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-THEME-

State of health lithium battery estimation using deep learning

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Loubna

DEDICATION

To my beloved family

Mom and Dad, whose endless love, support, and sacrifices have shaped the person I am today.

To my dear sister and my brother Zinou, for being my first friends and lifelong companions.

To my beautiful circle of friends who fill my life with light and laughter

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To everyone who has walked with me on this journey this is for you.

With gratitude, love, and memory, always.

Loubna

Abstract

The State of Health (SOH) of a lithium-ion battery is a critical metric used to evaluate the performance and degradation level of a battery compared to its original condition. It reflects the battery's ability to store and deliver energy effectively, and is often expressed as a percentage of its initial capacity. Accurate SOH estimation is crucial for ensuring battery reliability, safety, and efficiency, especially in sectors like electric vehicles (EVs), renewable energy storage, and portable electronics.

Traditional SOH estimation methods rely on electrochemical models, equivalent circuit models (ECMs), and statistical algorithms, which often require deep domain knowledge, detailed physical parameters, and controlled conditions. These approaches can be limited by their inability to handle real-world operating variability and may not scale well to different battery types or usage patterns.

To address these limitations, deep learning (DL) techniques have emerged as a promising alternative. Deep learning models, such as:

- Recurrent Neural Networks (RNNs)
- Long Short-Term Memory (LSTM) networks
- Convolutional Neural Networks (CNNs)
- Transformer architectures

...are capable of automatically learning the underlying patterns in large, complex datasets without the need for explicit modeling of the battery's internal behavior. These models can process multi-dimensional time-series data such as voltage, current, and temperature during charge/discharge cycles to estimate the SOH with high accuracy.

LSTM networks, in particular, have shown strong performance due to their ability to model time-dependent degradation trends over many cycles. Similarly, CNNs have been effectively used to extract features from battery data streams. Some advanced models even combine different deep learning architectures into hybrid frameworks to improve robustness and precision

- High accuracy in nonlinear and dynamic systems
- Adaptability to different battery chemistries and usage conditions
- Real-time, data-driven decision-making capability
- Reduced need for domain-specific knowledge or handcrafted features

However, deep learning approaches are not without challenges. These include:

- The need for large, high-quality labeled datasets for training
- Lack of transparency or interpretability in model predictions (black-box nature)
- High computational cost during training or deployment
- Generalization issues when applied to unseen or rare operating conditions

Recent research is addressing these limitations through transfer learning, explainable AI (XAI), and model compression techniques to make models more interpretable and suitable for embedded systems in real-world Battery Management Systems (BMS).

Keywords: state of health (SOH),lithium battery_deep learning_recurrent neural network(RNN)_long short term memory(LSTM)_convolution neural network(CNN)_transformer architecture_hybrid deep learning model_battery management system(BMS)_transfer learning_ explainable AI_model comparison

Résumé

L'état de santé (SOH) d'une batterie lithium-ion est un indicateur critique utilisé pour évaluer la performance et le niveau de dégradation d'une batterie par rapport à son état d'origine. Il reflète la capacité de la batterie à stocker et à fournir de l'énergie efficacement, et est souvent exprimé en pourcentage de sa capacité initiale. Une estimation précise du SOH est cruciale pour assurer la fiabilité, la sécurité et l'efficacité des batteries, en particulier dans des secteurs tels que les véhicules électriques (VE), le stockage d'énergie renouvelable et l'électronique portable.

Les méthodes traditionnelles d'estimation des SOH reposent sur des modèles électrochimiques, des modèles de circuits équivalents (ECM) et des algorithmes statistiques, qui nécessitent souvent une connaissance approfondie du domaine, des paramètres physiques détaillés et des conditions contrôlées. Ces approches peuvent être limitées par leur incapacité à gérer la variabilité de fonctionnement dans le monde réel et peuvent ne pas bien s'adapter aux différents types de batteries ou modes d'utilisation.

Pour répondre à ces limitations, les techniques d'apprentissage profond (DL) ont émergé comme une alternative prometteuse. Les modèles d'apprentissage profond, tels que :

- Réseaux de neurones récurrents (RNN)
- Réseaux de mémoire à court terme long (LSTM)
- Réseaux de neurones convolutifs (CNN)
- Architectures de transformateur

...sont capables d'apprendre automatiquement les motifs sous-jacents dans de grands ensembles de données complexes sans avoir besoin de modéliser explicitement le comportement interne de la batterie. Ces modèles peuvent traiter des données chronologiques multidimensionnelles telles que la tension, le courant et la température pendant les cycles de charge/décharge pour estimer le SOH avec une grande précision.

Les réseaux LSTM, en particulier, ont montré de solides performances grâce à leur capacité à modéliser les tendances de dégradation dépendantes du temps sur de nombreux cycles. De même, les CNN ont été efficacement utilisés pour extraire des fonctionnalités à partir de flux de données de batterie. Certains modèles avancés combinent même différentes architectures de deep learning dans des frameworks hybrides pour améliorer la robustesse et la précision

- Haute précision dans les systèmes non linéaires et dynamiques
- Adaptabilité à différentes chimies de batterie et conditions d'utilisation
- Capacité de prise de décision en temps réel, basée sur des données
- Besoin réduit de connaissances spécifiques au domaine ou de fonctionnalités artisanales

Cependant, les approches d'apprentissage profond ne sont pas sans défis. Ceux-ci incluent :

- Le besoin de grands ensembles de données étiquetés de haute qualité pour la formation
- Manque de transparence ou d'interprétabilité dans les prédictions du modèle (nature boîte noire)
- Coût computationnel élevé pendant la formation ou le déploiement
- Problèmes de généralisation lorsqu'ils sont appliqués à des conditions d'exploitation invisibles ou rares

Des recherches récentes s'attaquent à ces limites grâce à l'apprentissage par transfert, à l'IA explicable (XAI) et aux techniques de compression de modèles pour rendre les modèles plus interprétables et adaptés aux systèmes embarqués dans les systèmes de gestion de batterie (BMS) du monde réel.

Mots-clés :

État de santé (SOH), batterie lithium, apprentissage profond, réseau de neurones récurrent (RNN), mémoire à long terme de courte durée (LSTM), réseau de neurones convolutif (CNN), architecture Transformer, modèle hybride d'apprentissage profond, système de gestion de batterie (BMS), apprentissage par transfert, intelligence artificielle explicable, comparaison de modèles

الملخص

لبطارية الليثيوم أيون مقياسًا مهمًا يُستخدم لتقييم أداء البطارية ومستوى (SOH) تُعد الحالة الصحية
تدهورها مقارنةً بحالتها الأصلية. وهو يعكس قدرة البطارية على تخزين الطاقة وتوصيلها بفعالية، وغالباً ما يتم التعبير عنه كنسبة مئوية من سعتها الأولية. ويُعد التقدير الدقيق لسعة البطارية أمرًا بالغ الأهمية (EVs) لضمان موثوقية البطارية وسلامتها وكفاءتها، خاصةً في قطاعات مثل السيارات الكهربائية .وتخزين الطاقة المتجددة والإلكترونيات المحمولة

، (ECMs) التقليدية على النماذج الكهروكيميائية، ونماذج الدوائر المكافئة SOH تعتمد طرق تقدير والخوارزميات الإحصائية، والتي غالبًا ما تتطلب معرفة عميقة بالمجال، ومعلمات فيزيائية مفصلة، وظروف خاضعة للرقابة. يمكن أن تكون هذه الأساليب محدودة بسبب عدم قدرتها على التعامل مع تقلبات التشغيل في العالم الحقيقي وقد لا تتناسب بشكل جيد مع أنواع البطاريات المختلفة أو أنماط الاستخدام

(RNNs) الشبكات العصبية المتكررة -

(LSTM) شبكات الذاكرة طويلة المدى قصيرة المدى - (CNNs)

الشبكات العصبية التلافيفية -

البنى التحويلية -

قادرة على تعلم الأنماط الأساسية تلقائيًا في مجموعات البيانات الكبيرة والمعقدة دون الحاجة إلى نمذجة ... صريحة للسلوك الداخلي للبطارية. يمكن لهذه النماذج معالجة بيانات السلاسل الزمنية متعددة الأبعاد مثل .الجهد والتيار ودرجة الحرارة أثناء دورات الشحن/التفريغ لتقدير السوائل والماء بدقة عالية

، على وجه الخصوص، أداءً قويًا نظرًا لقدرتها على نمذجة اتجاهات LSTM وقد أظهرت شبكات بشكل CNN التدهور المعتمدة على الوقت على مدار العديد من الدورات. وبالمثل، استُخدمت شبكات فعال لاستخراج الميزات من تدفقات بيانات البطارية. حتى أن بعض النماذج المتقدمة تجمع بين بنيات التعلم العميق المختلفة في أطر هجينة لتحسين المتانة والدقة

دقة عالية في الأنظمة غير الخطية والديناميكية -

القدرة على التكيف مع كيميائيات البطاريات وظروف الاستخدام المختلفة - القدرة على اتخاذ القرارات في

الوقت الحقيقي المستندة إلى البيانات -

تقليل الحاجة إلى المعرفة الخاصة بالمجال أو الميزات المصنوعة يدوياً - :ومع ذلك، لا تخلو

مناهج التعلم العميق من التحديات. وتشمل هذه التحديات الحاجة إلى مجموعات بيانات موسومة

كبيرة وعالية الجودة للتدريب -

عدم الشفافية أو قابلية التفسير في تنبؤات النموذج (طبيعة الصندوق الأسود) - التكلفة الحسابية العالية أثناء

التدريب أو النشر -

مشاكل التعميم عند تطبيقها على ظروف التشغيل غير المرئية أو النادرة -

تعالج الأبحاث الحديثة هذه القيود من خلال التعلّم التحويلي والذكاء الاصطناعي القابل للتفسير وتقنيات ضغط النماذج لجعل النماذج أكثر قابلية للتفسير ومناسبة للأنظمة المدمجة في أنظمة إدارة البطاريات في العالم الحقيقي.

الكلمات المفتاحية:

الحالة الصحية (SOH)، الشبكات العصبية المتكررة (RNN)، بطارية الليثيوم، التعلم العميق، الشبكات العصبية التلافيفية (CNN)، الذاكرة طويلة وقصيرة المدى (LSTM)، الشبكات العصبية التلافيفية، بنية المحولات (Transformer)، نظام إدارة البطارية (BMS)، نموذج التعلم العميق الهجين، التعلم بالنقل، الذكاء الاصطناعي القابل للتفسير، مقارنة النماذج

Table of content

Figures List

Tables List

General Itroduction

General Introduction:

The State of Health (SOH) of lithium-ion batteries is a critical parameter that reflects their current condition relative to their original specifications. Accurate SOH estimation is essential for ensuring the safety, reliability, and longevity of battery-powered systems, particularly in electric vehicles (EVs) and renewable energy storage applications. Traditional methods for assessing SOH often involve time-consuming and costly experimental procedures, which may not be feasible for real-time monitoring or large-scale applications.

In recent years, deep learning techniques have emerged as powerful tools for estimating the SOH of lithium-ion batteries. These methods leverage large datasets to model complex relationships between battery performance indicators and their health status. Notable approaches include:

Long Short-Term Memory (LSTM) Networks: Effective in capturing temporal dependencies in battery data, such as charging and discharging cycles.

Convolutional Neural Networks (CNNs): Utilized for feature extraction from voltage and current profiles.

Vision Transformers (ViTs): Applied to analyze sequential battery data by treating them as image- like inputs.

Hybrid Models: Combining multiple deep learning architectures, such as CNN-LSTM or CNN-Transformer, to enhance prediction accuracy.

These deep learning models have demonstrated significant improvements in SOH estimation accuracy compared to traditional methods. For instance, a study by Li et al. (2025) introduced a hybrid model integrating attention mechanisms, CNNs, and LSTMs within an augmented neural ordinary differential equation framework, achieving root mean square errors (RMSE) as low as 1.01% and 2.24% on various datasets .

Moreover, the application of transfer learning has further enhanced the generalization capabilities of SOH estimation models. By fine-tuning pre-trained models on new datasets, transfer learning allows for effective SOH estimation across different battery types and operating conditions, even with limited labeled data .

The integration of deep learning techniques into Battery Management Systems (BMS) facilitates real- time, accurate monitoring of battery health, enabling proactive maintenance and optimizing battery usage. This advancement is crucial for the widespread adoption of electric vehicles and the efficient utilization of renewable energy storage systems.

Chaptre 01 : Deep Learing

CHAPTRE 01: DEEP LEARNING

Introduction:

In the rapidly evolving world of technology, the concepts of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have become integral to the development of innovative systems across various industries. AI refers to the broader field of computer science that focuses on creating machines capable of performing tasks that would typically require human intelligence, such as decision-making, reasoning, and problem-solving. Over time, AI has evolved from basic rule-based systems to complex, data-driven technologies that power everything from personal assistants like Siri and Alexa to autonomous vehcles and predictive healthcare solutions.

Machine Learning, a subset of AI, has significantly advanced the ability of machines to learn and improve from experience. Rather than being explicitly programmed for every task, ML systems use data to recognize patterns and make decisions. This shift from rule-based systems to data-driven models has opened up new possibilities in areas like natural language processing (NLP), image recognition, and personalized recommendations. ML algorithms have the ability to adapt and optimize themselves, making them extremely powerful tools in today's data-driven world.

Deep Learning, a further subset of Machine Learning, leverages complex architectures known as neural networks to model intricate patterns in large datasets. Unlike traditional ML models, which often require manual feature extraction, deep learning algorithms can automatically learn hierarchical representations of data. This characteristic makes deep learning especially effective in domains like speech recognition, computer vision, and even gaming. The success of deep learning is largely attributed to its ability to process unstructured data, such as images and text, and to solve problems that were once considered too difficult for machines to handle.

Among the many breakthroughs in deep learning, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have emerged as two of the most powerful and widely used models. CNNs are specialized neural networks designed to work with grid-like data, particularly images. They are widely used in computer vision tasks like object detection and image classification. On the other hand, LSTMs, a type of Recurrent Neural Network (RNN), are particularly suited for sequential data, such as time-series predictions or natural language processing, thanks to their ability to retain information over time and capture long-term dependencies.

This paper aims to provide a comprehensive overview of these key areas in artificial intelligence, exploring their foundations, relationships, applications, and the challenges they address. We will explore how these technologies have revolutionized various fields, from healthcare to entertainment, and how they are continuing to shape the future of intelligent systems. The goal is to understand the fundamental principles of AI, ML, and DL, as well as the specific roles that CNNs and LSTMs play in pushing the boundaries of what machines can achieve

1. Artificial intelligence:

Artificial Intelligence (AI): is the field of computer science dedicated to creating machines and systems that can perform tasks that typically require human intelligence. These tasks range from simple ones, like identifying objects in an image, to complex processes, such as understanding and generating natural language, or making decisions based on past experiences. AI seeks to replicate the cognitive abilities of the human mind, including learning, problem-solving, reasoning, and decision-making.

1.2 Definition and History of AI:

AI, as a concept, dates back to ancient times when philosophers and mathematicians attempted to understand the nature of intelligence and create mechanisms that could emulate human reasoning. However, it wasn't until the mid-20th century that AI became a formal field of study, thanks to key figures like Alan Turing, whose famous Turing Test laid the groundwork for thinking about machine intelligence. In 1956, the term "Artificial Intelligence" was coined by John McCarthy during the Dartmouth Conference, which is widely considered to be the birth of AI as a field.

Early AI systems were rule-based and could only perform specific tasks with predefined logic. These systems operated on limited data and were unable to adapt or learn from new information. Over the decades, AI evolved as researchers developed new approaches and algorithms. Notable milestones include the creation of expert systems in the 1970s and the development of machine learning algorithms in the 1990s, which enabled AI systems to learn from data rather than relying solely on pre-programmed rules

2. Machine Learning (ML):

Machine Learning (ML) is a subset of Artificial Intelligence (AI) that focuses on the development of algorithms that allow computers to learn from and make predictions or decisions based on data. Unlike traditional AI, where systems are explicitly programmed to perform specific tasks, machine learning systems use statistical methods to find patterns in data and improve their performance over time without being programmed for every decision. The core idea of ML is to enable machines to learn from experience and generalize that knowledge to new, unseen data.

2.1 Definition and Relationship with AI:

Machine Learning is often described as the practice of teaching computers to learn from data. It is distinct from traditional programming, where developers write explicit instructions for every task. Instead, in ML, the machine is trained using large datasets, from which it learns to identify patterns and make decisions autonomously.

The relationship between AI and ML can be understood as follows:

Artificial Intelligence is the broader concept that encompasses any technique that enables computers to mimic human intelligence.

Machine Learning is a subfield of AI focused on algorithms and statistical models that enable a system to improve its performance on a task through experience.

While AI involves reasoning, problem-solving, and decision-making, machine learning focuses specifically on learning from data to optimize decision-making and predictions.

2.2 Types of Machine Learning:

There are three primary types of machine learning: Supervised Learning, Unsupervised Learning, and Reinforcement Learning. Each has its own approach and application areas.

- **Supervised Learning:**

In supervised learning, the algorithm is trained using a labeled dataset, which means that the data includes both the input and the correct output (target). The goal is for the algorithm to learn a mapping from inputs to outputs, so that it can predict the output for new, unseen data.

Example:

Spam email classification, where emails are labeled as "spam" or "not spam." The algorithm learns from this labeled data and can then predict whether a new email is spam ommon Algorithms: Linear regression, Logistic regression, Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Decision Trees, and Random Forests.

- **Unsupervised Learning:**

In unsupervised learning, the algorithm is given data without labels or predefined outputs. The goal is for the model to identify patterns, relationships, or groupings within the data on its own.

Example:

Customer segmentation in marketing, where the algorithm clusters customers based on their purchasing behavior or demographics without any prior labels.

Common Algorithms: K-means clustering, Hierarchical clustering, Principal Component Analysis (PCA), and Autoencoders.

- **Reinforcement Learning:**

Reinforcement learning is an approach where an agent learns to make decisions by performing actions in an environment and receiving feedback in the form of rewards or penalties. The agent aims to maximize its cumulative reward over time by learning from its actions and experiences.

3. Deep Learning (DL):

Deep Learning (DL) is a subfield of Machine Learning (ML) that focuses on algorithms inspired by the structure and function of the human brain, particularly neural networks. Deep learning models use multiple layers of processing to learn complex representations of data, making them especially powerful for tasks like image recognition, speech processing, and natural language understanding. The term "deep" refers to the number of layers in the neural network, and these models can automatically learn intricate features from large datasets.

3.1 Definition and Background of Deep Learning:

Deep learning models are composed of neural networks with many layers, often referred to as artificial neural networks (ANNs). Each layer in a deep neural network learns increasingly abstract representations of the input data, building from basic features in the lower layers (such as edges in an image) to more complex features in higher layers (such as objects or scenes in the image).

The history of deep learning dates back to the 1940s with the development of the first neural network models. However, due to limitations in computational power and the availability of large datasets, early attempts at deep learning were not as successful. It wasn't until the 2000s, with advances in hardware (especially GPUs) and large-scale datasets, that deep learning models began to outperform traditional machine learning methods in various domains, such as computer vision and speech recognition.

The key breakthrough for deep learning was the development of techniques like backpropagation, which allows the model to adjust the weights of the neural network based on the errors between predicted and actual outcomes, thus improving its performance.

3.2 Key Components of Deep Learning:

Deep learning models are built on a foundation of several key components that allow them to automatically learn patterns from data:

Neural Networks: At the core of deep learning is the neural network, which is inspired by the brain's neural structure. A neural network consists of nodes (neurons) connected by edges (synapses), each having weights that adjust as the model learns. The most basic neural network consists of three types of layers:

Input layer: The first layer that receives the raw data.

Hidden layers: Intermediate layers where the model learns features from the data. A "deep" neural network typically has many hidden layers.

Output layer: The final layer that produces the model’s predictions or classifications.

Activation Functions: In each neuron, an activation function determines whether the information should be passed forward to the next layer. Common activation functions include:

Sigmoid: Maps inputs to a range between 0 and 1, often used in binary classification tasks.

ReLU (Rectified Linear Unit): Allows positive values to pass through unchanged while setting negative values to zero, which speeds up training and reduces the vanishing gradient problem.

Softmax: Converts the outputs of the final layer into probabilities, typically used for multiclass classification.

Backpropagation and Gradient Descent: These are essential techniques used to optimize the neural network. Backpropagation is an algorithm that helps the network learn by adjusting the weights through a process of forward pass, loss calculation, and backward pass. Gradient descent is an optimization method used to minimize the loss function by updating the weights iteratively.

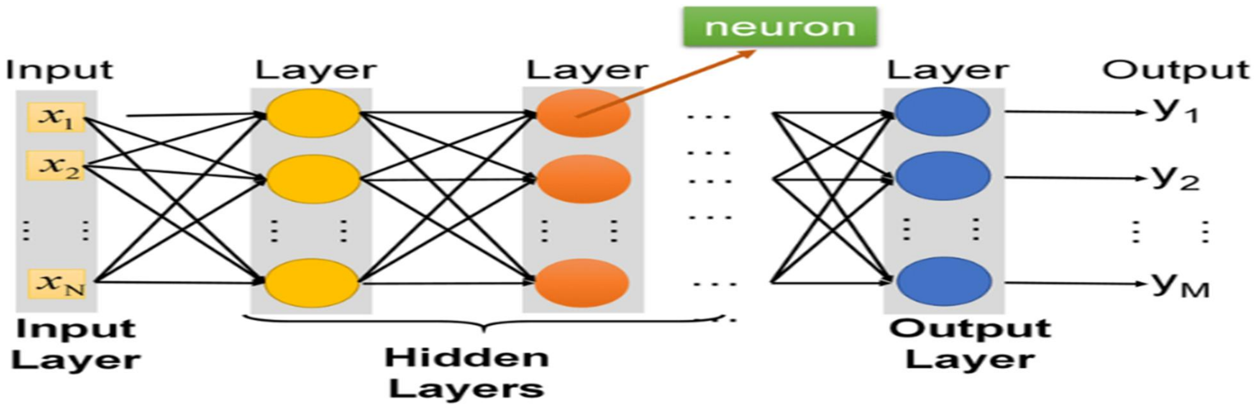

Figure 1.1: Architecture of Deep Neural Network

4. Convolutional Neural Networks (CNNs):

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed to process grid-like data, such as images, videos, and time-series data. CNNs are particularly powerful in tasks related to computer vision, including image classification, object detection, and facial recognition. They have revolutionized the way machines interpret visual data, making them one of the most widely used neural network architectures in modern AI applications.

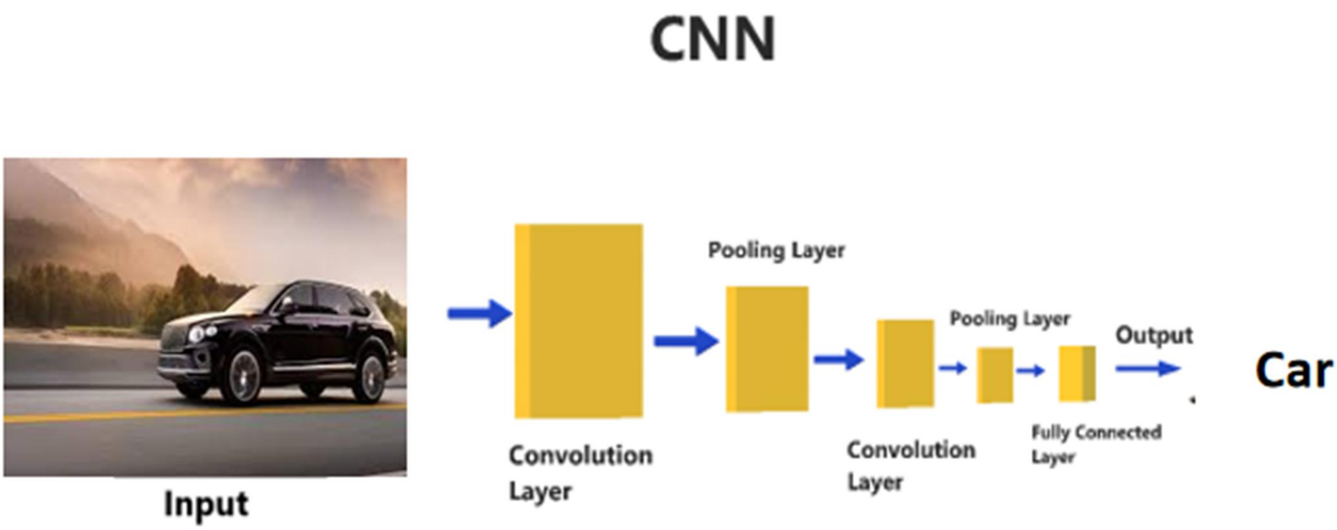

Figure 1.2: CNN Architectur

4.1 Definition and Structure of CNNs:

A CNN is a type of artificial neural network that uses convolutional layers, which apply a mathematical operation called convolution to the input data. This process allows the network to learn spatial hierarchies of features from the data. CNNs are designed to recognize patterns, such as edges, textures, and shapes, in a way that mimics how humans perceive visual information.

The structure of a CNN typically consists of the following layers:

i. Convolutional Layers:

These are the core building blocks of CNNs. A convolutional layer applies a series of filters (or kernels) to the input image, producing a set of feature maps. Each filter is designed to detect a specific feature, such as an edge, corner, or texture. The convolutional layer performs this operation by sliding the filter across the image and computing the dot product between the filter and the section of the image it is currently covering.

Activation function (usually ReLU) is applied to introduce non-linearity to the learned features.

1	0	-1
1	0	-1
1	0	-1

Figure 1.3: Example of 3x3 kernel

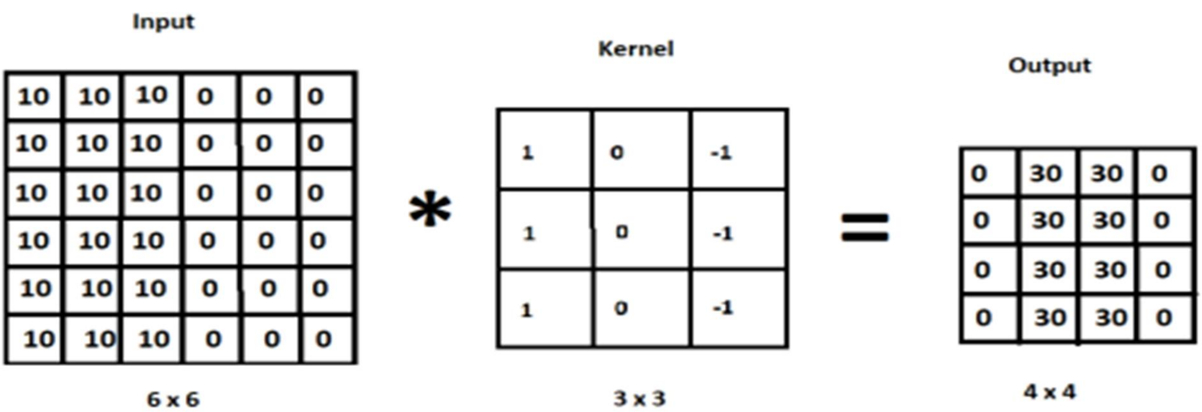

Figure 1.4: Example of convolutional operation with 6x6 image and 3x3 kernel

ii. Pooling Layers:

Pooling layers are used to downsample the feature maps produced by the convolutional layers. The most common form is max pooling, which selects the maximum value from a patch of the feature map, reducing its spatial dimensions. This process reduces the computational complexity and helps the network generalize better by retaining only the most important features.

Application: Pooling helps to make the network invariant to small translations and distortions in the input data.

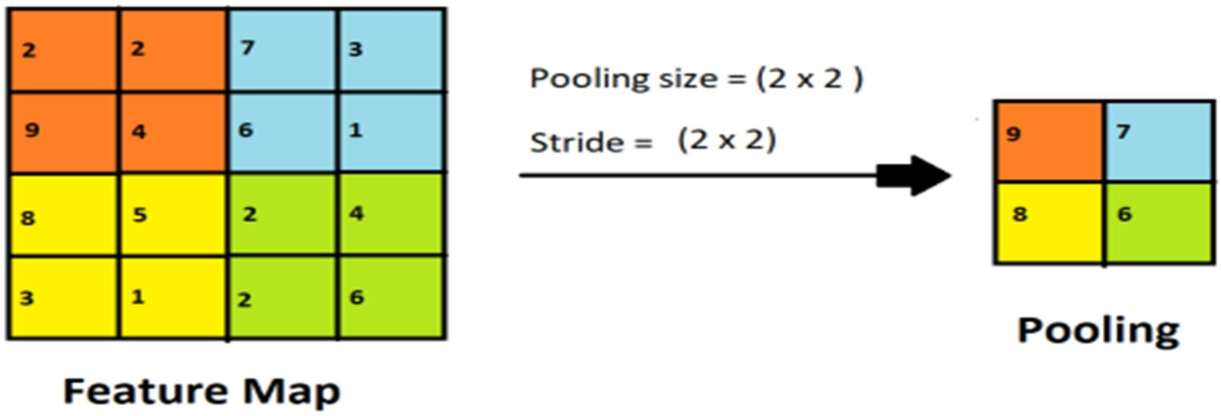

Figure 1.5: Examples of max pooling

iii. Fully Connected Layers:

After several convolutional and pooling layers, the high-level reasoning is carried out by fully connected layers. These layers are dense, meaning every neuron is connected to every neuron in the previous layer. The output of the final fully connected layer is typically a set of class scores (in classification tasks) or a regression value (in regression tasks).

The fully connected layers can be thought of as traditional neural network layers that make the final decision based on the features learned by the earlier convolutional and pooling layers.

iv. Normalization Layers (Optional):

Some CNNs include Batch Normalization layers, which standardize the inputs to each layer, improving the network's training speed and stability by reducing internal covariate shift.

v. Softmax Layer:

In the output layer, a Softmax activation function is often applied for classification tasks. It converts the output into probability distributions, making the network's predictions interpretable.

b. How CNNs Work:

CNNs work by automatically learning hierarchical features from data. Each layer in the network learns increasingly abstract representations of the data:

In the initial layers, the network learns basic features, such as edges, corners, and textures.

In the intermediate layers, the network begins to detect more complex patterns, such as shapes or parts of objects (e.g., wheels, eyes, or ears).

In the deeper layers, the network combines these complex features to recognize high-level concepts, such as specific objects or scenes.

Through this hierarchical learning process, CNNs can effectively process and recognize complex structures in data, such as images, and perform tasks like classification or detection.

c. Key Advantages of CNNs:

CNNs offer several advantages that make them particularly suitable for image and visual data processing:

Translation Invariance: CNNs can recognize features in an image regardless of their position, thanks to the sliding window approach used in convolution. This makes CNNs robust to slight translations or shifts in the input image.

Parameter Sharing: Instead of learning a separate parameter for each pixel, CNNs use shared weights in their convolutional filters, significantly reducing the number of parameters and making them computationally efficient.

Hierarchical Feature Learning: CNNs learn features at multiple levels of abstraction, from simple edges in lower layers to complex objects in higher layers, making them highly effective for tasks that require recognizing intricate patterns.

Scalability: CNNs can scale effectively to larger datasets and more complex models, making them suitable for large-scale tasks, such as image classification in millions of categories or detecting multiple objects in an image.

4.2 Applications of CNNs:

CNNs have achieved state-of-the-art performance in a variety of applications, primarily in computer vision but also in other areas involving grid-like data.

i. Image Classification:

CNNs are widely used for image classification tasks, where the goal is to assign a label to an image based on its content. For example, given an image of a cat, a CNN might classify it as "cat," while an image of a dog might be classified as "dog."

Application: Recognizing handwritten digits (MNIST dataset), classifying medical images (e.g., detecting tumors in X-rays or MRIs).

5. Long Short-Term Memory (LSTM):

Long Short-Term Memory (LSTM) is a specialized type of Recurrent Neural Network (RNN) designed to address the problem of learning long-term dependencies in sequential data. While traditional RNNs have been effective for tasks involving sequences (such as time-series analysis or language modeling), they suffer from issues like the vanishing gradient problem, which prevents them from learning long-term dependencies. LSTMs were specifically designed to overcome this limitation, making them highly successful in tasks such as natural language processing, speech recognition, and time-series forecasting.

5.1 Overview of LSTM:

LSTM networks are a type of Recurrent Neural Network (RNN). RNNs are designed for processing sequential data by maintaining an internal state or memory that can persist information over time. However, standard RNNs face difficulties in learning long-term dependencies due to the way gradients are propagated during backpropagation through time (BPTT), leading to either exploding or vanishing gradients.

LSTM networks address this problem by introducing a more complex architecture that includes gates which control the flow of information through the network. These gates enable the model to retain important information over long sequences and "forget" irrelevant information.

5.2 The Architecture of LSTM:

LSTM networks consist of several components that work together to enable the model to retain or forget information at each time step:

i. Cell State:

The cell state acts as a conveyor belt that runs through the entire chain of the LSTM network. It carries the relevant information throughout the sequence, allowing the model to retain long-term dependencies. The cell state is modified at each time step by the gates.

ii. Gates:

LSTMs use gates to control the flow of information into and out of the cell state. The gates are sigmoid functions that output values between 0 and 1, determining how much of the information should be passed through. The three primary gates in an LSTM are:

Forget Gate: Decides which information from the previous time step should be discarded or "forgotten." It looks at the previous hidden state and the current input and outputs a value between 0 and 1, where 0 means "completely forget" and 1 means "completely retain."

Input Gate: Controls how much new information should be added to the cell state. It also decides which values should be updated and saved to the cell state.

Output Gate: Determines what the next hidden state (output) should be. It decides which part of the cell state should be output as the hidden state for the current time step, which will also be used as the input for the next time step.

The combination of these gates enables LSTMs to regulate the flow of information, ensuring that the network retains relevant information over long sequences while forgetting irrelevant data.

5.3 How LSTMs Work:

At each time step, an LSTM network performs the following operations:

iii. Forget Gate:

The forget gate takes the previous hidden state ($h_{(t-1)}$) and the current input (x_t) and outputs a value between 0 and 1 for each number in the cell state $C_{(t-1)}$. This value decides which information from the previous cell state should be discarded.

iv. Input Gate:

The input gate decides what new information should be stored in the cell state. The output of the input gate is combined with a candidate value, and the new information is added to the cell state after being scaled by the input gate's output.

v. Update Cell State:

The cell state is updated by combining the output of the forget gate (which determines what to "forget") and the output of the input gate (which decides what to "remember").

vi. Output Gate:

The output gate determines the final output (h_t) at the current time step. This output is based on the updated cell state and is passed through a tanh function (to scale the output between -1 and 1) and then multiplied by the output of the sigmoid function.

This sequence of operations ensures that LSTMs can store information for longer periods, selectively forgetting or updating data as needed. The use of gates helps avoid the vanishing gradient problem, which makes LSTMs well-suited for learning long-term dependencies.

b. Advantages of LSTM:

LSTMs provide several advantages over traditional RNNs and other types of neural networks:

Solving the Vanishing Gradient Problem: One of the most significant issues with traditional RNNs is the vanishing gradient problem, where gradients become extremely small during backpropagation through time, making it difficult for the network to learn long-range dependencies. LSTMs, with their cell state and gating mechanisms, mitigate this problem by allowing gradients to flow more effectively over many time steps.

Learning Long-Term Dependencies: LSTMs are explicitly designed to retain information over long periods of time. This makes them particularly effective for tasks where the current output depends on information from many time steps earlier in the sequence.

Flexibility: LSTMs can be applied to various types of sequential data, from time-series data to text and speech. Their ability to model dependencies at different time scales makes them versatile in handling different types of problems.

5.4 Applications of LSTM:

LSTMs have found widespread applications across various fields due to their ability to process sequential data effectively:

Natural Language Processing (NLP):

LSTMs have been widely used in NLP tasks such as machine translation, speech recognition, and text generation. LSTMs can model the dependencies between words and phrases over long sentences, which is crucial for understanding context in language.

Application: Machine translation (e.g., Google Translate), speech-to-text systems (e.g., voice assistants), and language modeling.

Time-Series Forecasting:

LSTMs excel at tasks involving time-series data, such as predicting stock prices, weather forecasting, and demand forecasting. The ability to learn from historical data and predict future values makes LSTMs ideal for these tasks.

Application: Financial forecasting, predicting energy consumption, and sales prediction.

Speech Recognition:

In speech recognition, LSTMs can learn the sequential nature of speech and model the relationship between phonemes, words, and sentences. This is crucial for accurately transcribing spoken language into text.

Application: Virtual assistants (e.g., Siri, Alexa), transcription services, and real-time translation systems.

Video Analysis:

LSTMs can be used to analyze video data by learning temporal patterns across frames. This allows them to recognize actions or events that span multiple frames, which is useful for tasks like activity recognition or video summarization.

Application: Video surveillance (e.g., detecting suspicious behavior), activity recognition in sports or entertainment, and video captioning.

Anomaly Detection:

LSTMs are also useful for anomaly detection, especially in time-series data. By learning the normal patterns of a system, LSTMs can detect deviations that may indicate faults or unusual behavior.

Application: Predictive maintenance (e.g., detecting equipment failures in industrial settings), fraud detection (e.g., in financial transactions), and health monitoring.

5.5 Challenges and Limitations of LSTM:

Despite their effectiveness, LSTMs are not without limitations:

Complexity: LSTMs are more computationally expensive than traditional RNNs due to their complex architecture, especially when dealing with long sequences or large datasets. Training LSTM models requires significant computational resources, often necessitating powerful hardware (e.g., GPUs).

Overfitting: LSTM networks can easily overfit, particularly when there is a limited amount of training data. To mitigate overfitting, techniques such as dropout or early stopping are often employed.

Training Time: Due to their complexity, training LSTMs can take longer compared to simpler models. Optimizing LSTM parameters requires more time and computational resources, especially for large-scale problems.

5.6 Future Directions for LSTM:

Although LSTMs have been highly successful, several advancements and alternatives are being explored to improve upon or complement LSTM models:

Attention Mechanisms:

The attention mechanism has become a powerful addition to LSTMs, especially in tasks like machine translation and text summarization. Attention allows the model to focus on specific parts of the input sequence, enabling it to learn more relevant information at each step.

Application: Transformer models, such as BERT and GPT, which use attention mechanisms and have surpassed LSTMs in many NLP tasks.

Gated Recurrent Units (GRUs):

GRUs are a simplified variant of LSTMs, using fewer gates and parameters. They have been shown to perform similarly to LSTMs while requiring less computational power, making them a good alternative for some tasks.

Neural Architecture Search:

Researchers are exploring ways to automatically search for optimal neural network architectures. This can lead to more efficient versions of LSTMs and other models, reducing the need for manual tuning.

Conclusion of Deep Learning:

Deep learning has transformed the landscape of artificial intelligence (AI), driving significant advancements in various fields such as computer vision, natural language processing, speech recognition, and robotics. The development of deep learning models, especially neural networks like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, has enabled machines to solve complex tasks with a level of accuracy and efficiency previously unimaginable.

One of the key factors behind the success of deep learning is its ability to learn hierarchical features directly from data, eliminating the need for manual feature extraction. This ability to automatically extract and learn relevant features has made deep learning models highly effective across a wide range of applications, from recognizing objects in images to translating text across languages.

Moreover, the increasing availability of large datasets and the advancement of computational power, especially through GPUs, have played a pivotal role in the rise of deep learning. These models are no longer confined to academia or research labs but have become integral to industry applications, enhancing user experiences, improving business operations, and enabling new innovations.

However, deep learning is not without its challenges. Models can be computationally expensive to train, require vast amounts of labeled data, and, despite their success, often remain "black boxes" that are difficult to interpret. Additionally, deep learning models can suffer from issues like overfitting, and their performance is highly dependent on the quality of the data used for training.

Looking ahead, deep learning is expected to continue evolving, with research focused on improving model efficiency, interpretability, and robustness. New techniques such as transfer learning, generative models (e.g., GANs), and reinforcement learning are already pushing the boundaries of what deep learning models can achieve. Furthermore, the integration of deep learning with other AI paradigms, like symbolic reasoning and explainable AI, promises to create even more powerful and adaptable systems.

In conclusion, deep learning represents one of the most significant breakthroughs in the field of AI, offering powerful tools to solve real-world problems.

As technology continues to advance the potential applications and impact of deep learning will only grow, making it a cornerstone of the future of AI and machine learning.

Chapter 02 : Battery

CHAPTRE 02 : BATTERY

Introduction:

Batteries are essential energy storage devices that convert chemical energy into electrical energy. They play a critical role in modern life, powering everything from smartphones and laptops to electric vehicles and large-scale renewable energy systems. Batteries come in various types and sizes, ranging from small coin cells used in watches to large lithium-ion packs in electric cars and grid storage facilities.

The basic structure of a battery consists of three main components: an anode (negative electrode), a cathode (positive electrode), and an electrolyte that allows ions to move between the electrodes. When a battery is connected to a circuit, a chemical reaction occurs between the electrodes and the electrolyte, releasing electrons that flow through the external circuit, providing electrical power.

Batteries can be broadly categorized into two types: primary batteries, which are single-use and non-rechargeable (like alkaline batteries), and secondary batteries, which are rechargeable (such as lithium-ion and lead-acid batteries).

With the global shift toward clean energy and sustainable technologies, battery development has become a major focus. Innovations aim to improve energy density, charging speed, lifespan, safety, and environmental impact. The growth of electric vehicles (EVs), portable electronics, and renewable energy systems is driving the demand for more efficient and reliable battery technologies.

1. Batteries:

Batteries are electrochemical devices that store and release electrical energy through reversible chemical reactions. Each battery comprises one or more electrochemical cells, each consisting of an anode (negative electrode), a cathode (positive electrode), and an electrolyte that facilitates ion movement between the electrodes. During discharge, oxidation occurs at the anode, releasing electrons that flow through an external circuit to the cathode, where reduction takes place. This movement of electrons provides electrical power to connected devices.

Batteries are classified into two main categories: primary (non-rechargeable) and secondary (rechargeable). Primary batteries, such as zinc-carbon and alkaline cells, are designed for single-use applications. Secondary batteries, including lead-acid, nickel-cadmium (NiCd), nickel-metal hydride (NiMH), and lithium-ion (Li-ion) batteries, can undergo multiple charge and discharge cycles, making them suitable for applications requiring sustained energy supply.

The development of battery technologies has been driven by the need for efficient energy storage solutions in various sectors, including consumer electronics, electric vehicles, and renewable energy systems. Lithium-ion batteries, in particular, have gained prominence due to their high energy density, long cycle life, and relatively low self-discharge rates. However, challenges such as cost, safety concerns, and environmental impact continue to spur research into alternative chemistries and next-generation battery technologies

2. Lithium-Ion Battery

A lithium-ion (Li-ion) battery is a type of rechargeable electrochemical cell that stores and releases electrical energy through the reversible intercalation and deintercalation of lithium ions (Li^+) between the anode and cathode. During discharge, lithium ions migrate from the anode to the cathode through the electrolyte, generating a flow of electrons in the external circuit that powers connected devices. Upon charging, the process is reversed, with lithium ions moving back to the anode, thereby restoring the battery's energy capacity.

Li-ion batteries are characterized by their high energy density, long cycle life, and relatively low self-discharge rates compared to other rechargeable batteries. These attributes make them suitable for a wide range of applications, including portable electronics, electric vehicles, and grid-scale energy storage systems. The development and commercialization of Li-ion batteries have been pivotal in advancing modern technology, as recognized by the 2019 Nobel Prize in Chemistry awarded to M. Stanley Whittingham, John B. Goodenough, and Akira Yoshino for their contributions to the invention of the rechargeable lithium-ion battery

3. Challenges of Lithium-Ion Batteries:

Lithium-ion batteries (LIBs) have revolutionized energy storage across various sectors, including consumer electronics, electric vehicles, and renewable energy systems. However, several critical issues hinder their optimal performance, safety, and environmental sustainability.

3.1 Safety Concerns: Thermal Runaway and Fires

LIBs are susceptible to thermal runaway—a chain reaction leading to overheating, fires, or explosions. This phenomenon can be triggered by factors such as mechanical damage, internal short circuits, or exposure to high temperatures. Notable incidents, like the Samsung Galaxy Note 7 fires and Tesla vehicle battery failures, underscore the severity of these risks. To mitigate such hazards, researchers are exploring intrinsic safety mechanisms, including flame- retardant electrolytes and robust cell designs.

3.2 Degradation and Limited Lifespan:

Over time, LIBs experience capacity fade due to factors like electrode material degradation and electrolyte breakdown. This degradation leads to reduced battery life and performance. Advanced degradation estimation techniques and data-driven models are being developed to predict battery lifespan more accurately and to design batteries with enhanced durability.

3.3 Environmental and Health Impacts:

The production and disposal of LIBs pose environmental challenges. The use of toxic substances, such as bis-FASI, a subclass of per- and polyfluoroalkyl substances (PFAS), in battery manufacturing has been linked to pollution and health risks. These "forever chemicals" persist in the environment and can accumulate in living organisms, leading to potential long-term health effects.

3.4 Performance Issues in Electric Vehicles:

In electric vehicles (EVs), LIBs face challenges related to energy density, charging times, and performance under varying temperatures. These factors can affect the driving range and reliability of EVs. Ongoing research aims to develop alternative battery technologies and improve existing LIBs to meet the growing demands of the automotive industry.

4. State of the Art:

4.1 Definition of State of the Art:

The term "state of the art" refers to the highest level of development or achievement in a particular field, device, technique, or scientific discipline at a specific point in time. It encompasses the most advanced and innovative practices, technologies, or methodologies currently available. In academic and research contexts, a "state-of-the-art" review or analysis systematically examines and synthesizes the most recent and relevant literature to provide an up-to-date understanding of a subject area.

4.2 Purpose and Importance:

Conducting a state-of-the-art review serves several critical functions:

Establishing Context: It provides a comprehensive overview of existing knowledge, highlighting foundational theories, methodologies, and findings.

Identifying Gaps: By analyzing current research, it helps pinpoint areas lacking sufficient investigation or where further exploration is needed.

Guiding Future Research: It offers insights into emerging trends and potential directions for future studies.

Demonstrating Novelty: In research and development, it underscores the originality and significance of new contributions by contrasting them with existing work .

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4.3 Methodology:

A state-of-the-art review typically follows a structured approach:

Literature Search: Systematically searching academic databases using specific keywords and criteria to gather relevant studies.

Selection and Evaluation: Critically assessing the quality and relevance of identified studies to ensure their inclusion.

Synthesis: Organizing and integrating findings to identify patterns, trends, and relationships within the literature.

Analysis: Interpreting the synthesized information to draw conclusions about the current state of knowledge and identify areas for further research.

4.4 Applications:

State-of-the-art analyses are prevalent across various disciplines, including:

Engineering and Technology: Assessing the latest advancements in materials, processes, and systems.

Medicine and Healthcare: Reviewing current diagnostic methods, treatments, and technologies.

Environmental Science: Evaluating contemporary approaches to sustainability and conservation.

Social Sciences: Analyzing prevailing theories and methodologies in areas like psychology, sociology, and economics.

Conclusion:

Batteries are fundamental to modern technology, enabling portable energy storage for applications ranging from mobile electronics to electric vehicles and renewable energy systems. At the core of this innovation is the lithium-ion battery, a widely used rechargeable technology prized for its high energy density, long cycle life, and efficiency.

Despite their advantages, lithium-ion batteries face several challenges. Safety risks such as thermal runaway and fire hazards, performance degradation over time, environmental concerns from toxic materials, and limitations in energy density present ongoing obstacles to their broader and more sustainable use. These issues are driving intensive research into safer materials, more efficient chemistries, and better recycling practices.

Understanding the state of the art in battery technology is essential for researchers, engineers, and policymakers. It provides a snapshot of the most advanced developments and identifies both achievements and unresolved problems in the field. Through critical review and synthesis of current knowledge, the state-of-the-art approach informs innovation and guides the design of next-generation energy storage solutions.

In conclusion, while battery technology—especially lithium-ion—has transformed the way we store and use energy, continuous advancements are necessary to address its limitations. Future breakthroughs will depend on interdisciplinary research, sustainable practices, and a clear understanding of current technological frontiers.

Chapter 03 : Prognostics of the Lithium_ion Battery based on deep Learing Algorithms Comparative Study

Chaptre 03 : Prognostics of the Lithium_ion Battery based on deep Learing Algorithms Comparative Study

Abstract—Precise predictions of the remaining useful life (RUL) of batteries are becoming increasingly vital in intelligent battery health management systems. Progress in deep learning offers novel data-driven methodologies to address this issue. This paper presents a comprehensive deep learning methodology for forecasting the remaining useful life of batteries through the utilization of deep neural networks (DNNs). Initially, data are acquired from the NASA Li-batteries. A deep neural network is trained using the remaining useful life prediction model for batteries. This methodology is utilized across multiple deep learning models, and the comparative analysis of the results indicates that the CNN-LSTM model yields superior accuracy, necessitating further efforts to enhance these models for improved remaining useful life prediction. keywords—Predictive maintenance (PdM), Lithium-ionBattery, State of Health (SoH), Deep neural networks

Introduction

The escalating global energy crisis and environmental concerns have accelerated the rapid development of new energy technologies over the past decade, including Electric Vehicles (EVs), Hybrid Electric Vehicles (HEVs), and Micro grids. Among the key components of these systems, lithium-ion batteries (LIBs) stand out due to their high energy density, low environmental impact, and extended lifespan, making them a widely adopted energy storage solution [2], [3], [7], [17]. Throughout its life cycle, a battery undergoes changes in its electrical characteristics, directly influencing its remaining useful life (RUL), the time span from the present moment until it reaches the end of its functional capacity [14]. As highlighted in Refs [13], [16], fluctuations in a battery's RUL also impact its overall safety and stability. Therefore, accurately estimating the RUL of lithium-ion batteries is crucial for predicting performance variations, optimizing battery management strategies, extending operational longevity, and ensuring a safe and reliable energy system. Recognized as a high-energy rechargeable power source for smart manufacturing, lithium-ion batteries are valued for their large capacity, reliability, and safety, making them integral to applications in computational engineering, logistics, and aerospace industries. However, battery degradation can significantly impair device performance and lead to unexpected maintenance costs. Extended discharge cycles contribute to deterioration, reducing battery lifespan and potentially leading to critical failures or hazardous incidents [18]. Thus, accurately predicting the Remaining Useful Life (RUL) defined as the time remaining until a battery reaches the end of its useful life [15] is essential for enhancing safety, stability, and cost efficiency in intelligent manufacturing. This requires analyzing operational battery data to forecast degradation trends. Currently, LIB RUL prediction primarily relies on model-driven and data-driven approaches, each offering distinct advantages in predicting battery health and optimizing its life cycle.

1. The Proposed Methodology

1.1 Employment of Deep Learning to Prognostic Data

The field of diagnostics and prognostics is evolving with the integration of deep learning, shifting from traditional fault detection and failure diagnosis to more advanced techniques such as degradation pattern recognition and timeseries predictive analysis. Initially, modeling approaches relied on single algorithms like Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs). However, recent advancements have led to the development of hybrid models that integrate multiple layer types and traditional algorithms to enhance predictive accuracy. Over the years, the application of deep learning has expanded significantly, encompassing machinery, electrical and electronic systems, wind energy, and advanced aerospace technology [19]. In this study, Deep Neural Networks (DNNs) were exclusively employed to model the State of Health (SoH) and Remaining Useful Life (RUL) of lithium-ion batteries, rather than relying on conventional machine learning methods. Each deep learning approach offers distinct advantages and limitations. For instance, Artificial Neural Networks (ANNs) and DNNs are particularly effective in processing one-dimensional data, while CNNs excel in handling multidimensional data through various convolutional techniques. On the other hand, RNNs are well-suited for tasks involving time-series data or dependent inputs, whereas DNNs are generally preferred for extracting global features from fault data, making them particularly suitable for analyzing lithium-ion battery performance.

Additionally, as previously noted, CNN and RNN architectures are significantly more complex than DNNs, requiring longer training times, which is one of their primary limitations. Due to these considerations, DNNs are often the preferred choice in practical applications, as they offer a balance between computational efficiency and predictive performance.

A. CNN

The 1D Convolutional Neural Network employs two convolutional layers (64 and 128 filters with kernel size 3) for local feature extraction from the capacity sequences. Each convolution is followed by max pooling (pool size = 2) to reduce dimensionality. The extracted features are flattened and passed through a 100-unit dense layer before final regression output. This architecture excels at capturing local degradation patterns but lacks explicit memory mechanisms for long-term dependencies. Padding was adjusted to maintain valid sequence lengths throughout the network.

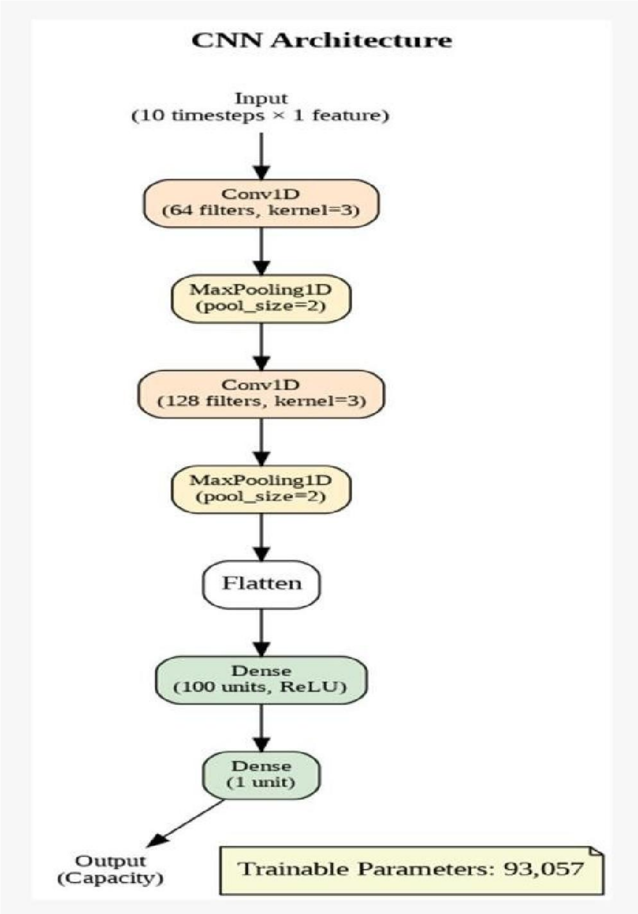


Figure 2.1: CNN model architecture

B. LSTM

The Long Short-Term Memory (LSTM) network employs a three-layer stacked architecture with 200 units per layer to capture temporal dependencies in battery capacity degradation. Each LSTM layer is followed by a 30% dropout regularization to prevent overfitting. The model processes sequences of 10 consecutive normalized capacity measurements (window size = 10) and outputs a single capacity prediction. The architecture's gating mechanisms (input, forget, and output gates) enable selective retention of long-term degradation patterns while filtering short-term fluctuations. Adam optimization with mean squared error loss was used for training

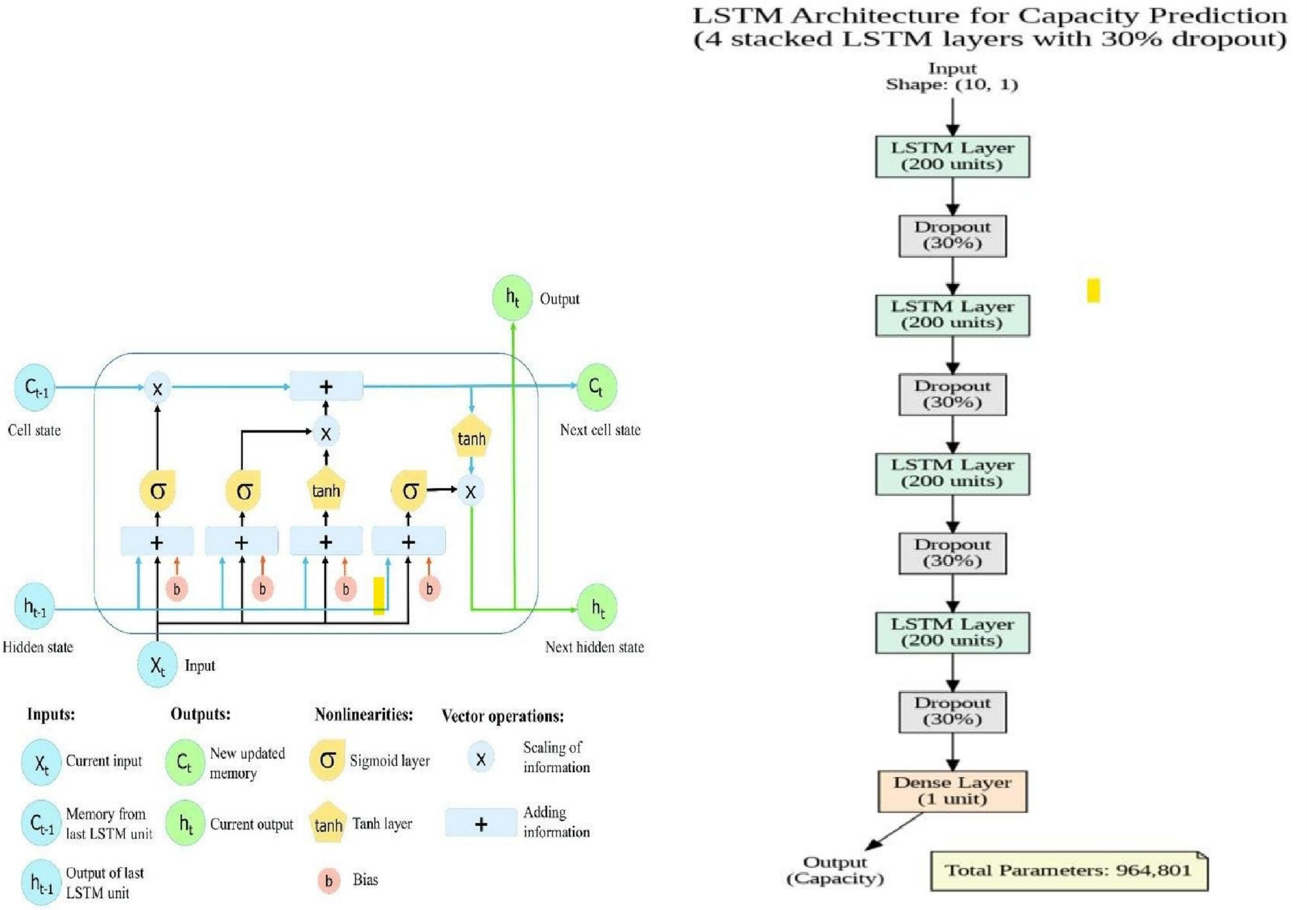


Figure 2.2: LSTM model architecture

C. GRU

The Gated Recurrent Unit (GRU) model implements a simplified gating mechanism compared to LSTM, with two stacked layers of 200 units each. This architecture maintains the sequence processing capability while reducing computational complexity through its update and reset gates. A 30% dropout between layers provides regularization. The GRU processes the same 10-cycle capacity sequences as the LSTM, making their performance directly comparable. The model was trained using Adam optimizer with MSE loss, identical to the LSTM configuration for fair comparison.

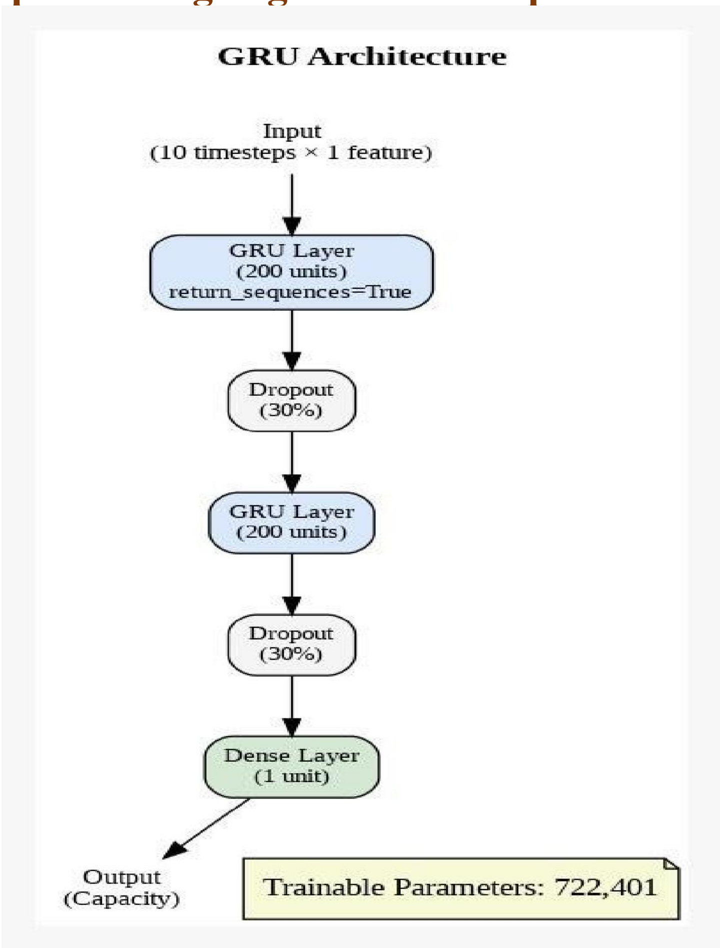


Figure 2.3: GRU model architecture

D. LSTM-CNN Hybrid Model:

Our hybrid architecture combines convolutional feature extraction with recurrent sequence processing. Two 1D convolutional layers (64 and 128 filters) with 'same' padding maintain the input sequence length, followed by two LSTM layers (200 units each). This design first extracts local temporal features through convolutions, then processes the refined sequence through LSTM gates. The model addresses both local pattern recognition and long-term dependency modeling, with 30% dropout between LSTM layers for regularization. Max pooling was limited to pool size 1 to preserve sequence length

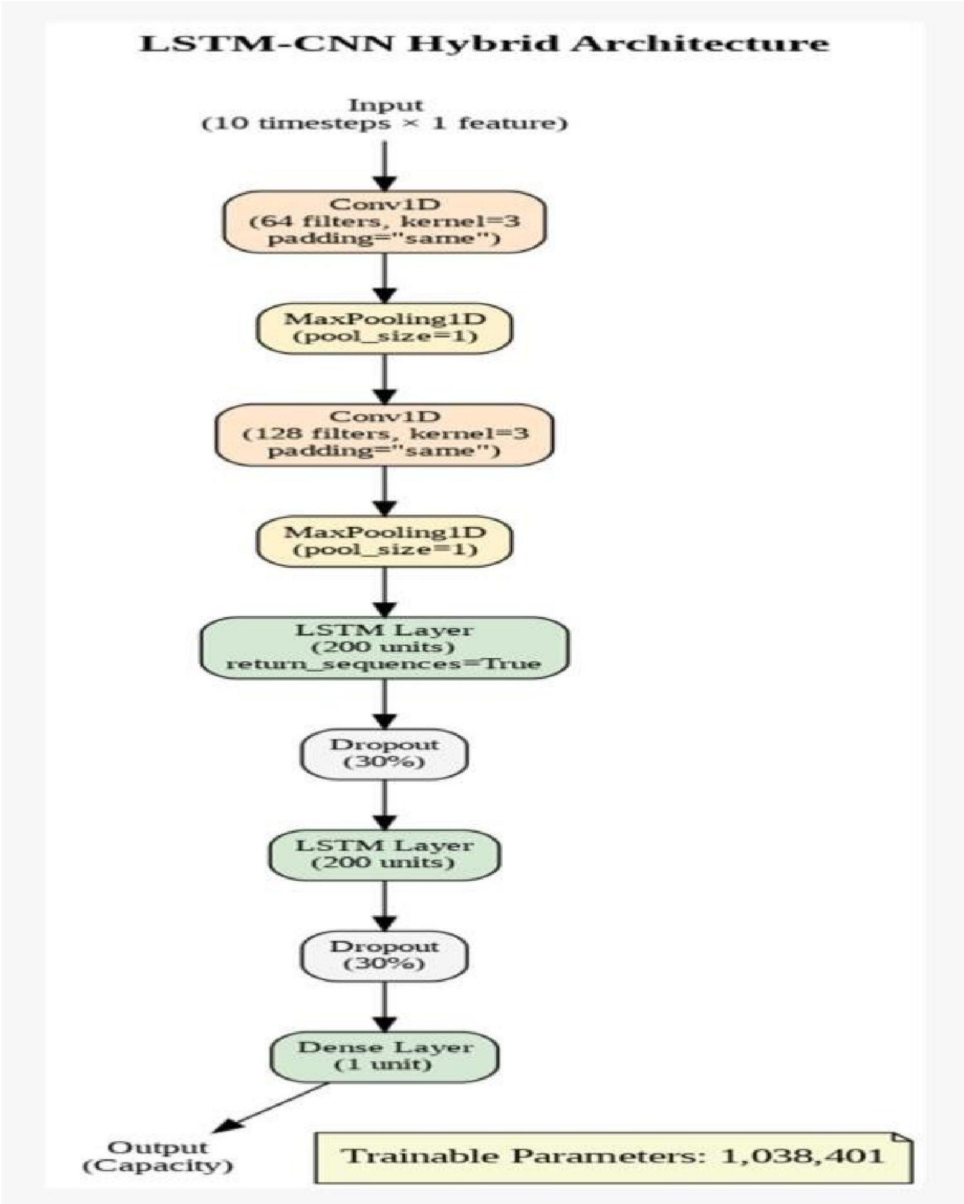


Figure 2.4: LSTM- CNN Hybrid architecture

E. DNN model:

The feedforward neural network processes instantaneous battery measurements (voltage, current, temperature) rather than temporal sequences. With three hidden layers (8 units each, ReLU activation), it learns nonlinear relationships between concurrent sensor readings and SOH. A 25% dropout layer precedes the linear output to prevent overfitting. Unlike sequence models, the DNN treats each cycle independently, making it computationally lighter but unable to capture temporal degradation patterns. Adam optimizer with MAE loss was used for training

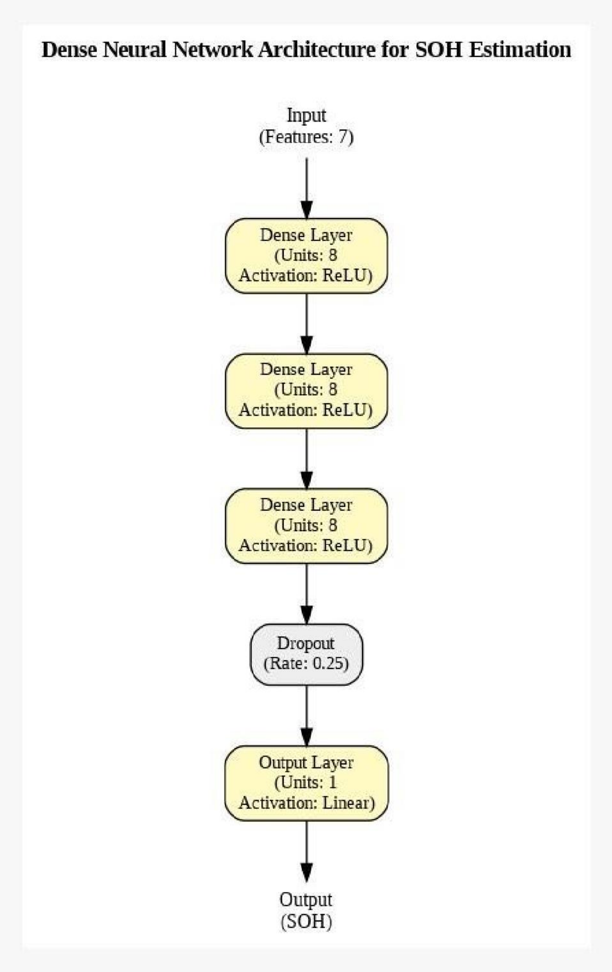


Figure 2.1: DNN model architecture

2. Experimental setup

A. Data description

This study utilizes NASA's lithium-ion battery dataset [10], where the rated capacity of the Li-ion battery is 2Ah. The analysis focuses on three batteries (B05, B06, and B07), with a failure threshold set at 70% of the initial capacity. The nominal rated capacity of these batteries is 2Ah, and failure is defined as reaching 0.7 times the initial capacity, setting the end-of-life threshold at 1.4Ah. Figure 1 demonstrates the use of the nonlinear least squares method to model the capacity degradation of lithium-ion batteries (LIBs). The results indicate that an exponential model provides a better fit for capacity degradation data, accurately capturing the overall trend of capacity decline and effectively reflecting the underlying degradation patterns.

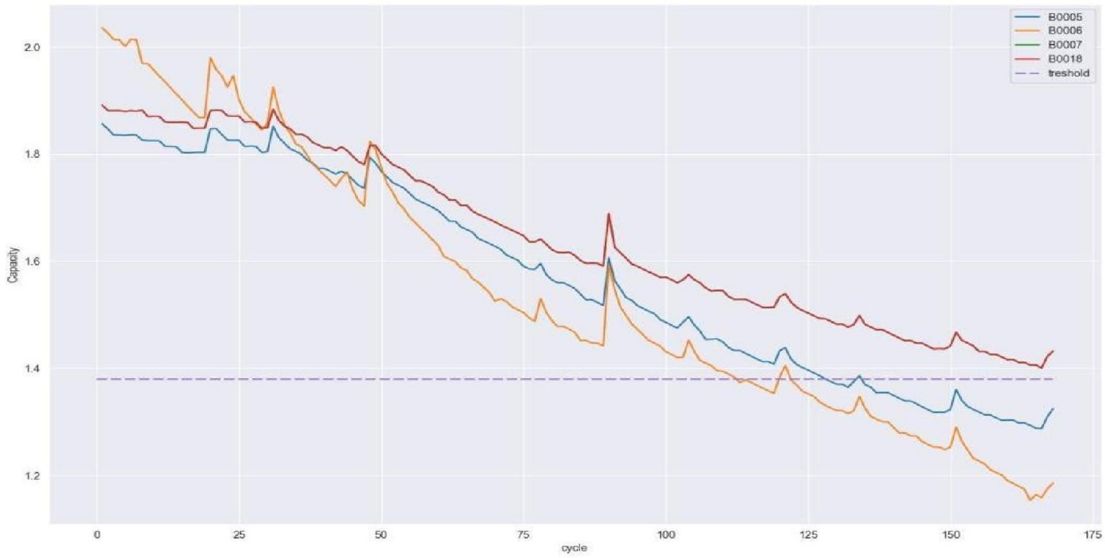


Figure 2.2: The capacity degradation curves of batteries

B. Prognostics of the Lithium-ion Battery

To evaluate battery prognostics, it is crucial to determine the State of Health (SoH), as predictions about battery performance often depend on this parameter. The SoH serves as a key predictive feature in the proposed data-driven model, alongside Remaining Useful Life (RUL). A clear understanding of SoH is essential, as it plays a fundamental role in predictive modeling. In this study, all attributes from the test dataset will be used as training features.

The following sections will explore specific battery attributes (or parameters), including definitions of State of Charge (SoC) and State of Health (SoH), to support prognostic analysis. The parameter Cmax,p represents the maximum practical capacity of the battery at a given moment. Over time, Cmax,p gradually decreases due to battery aging, impacting overall battery performance and longevity. SoH is another important parameter for battery health management. SoH is the direct indication of the health condition of the battery system. SoH can be generally defined as:

$$\text{SoH} = \frac{C_{\text{max},p}}{C_N}$$

estimating Cmax,p is a critical aspect of battery prognostics and health management, as it is essential for determining the State of Health (SoH), as referenced in Equation (1). The analyzed battery dataset included all aging data, with SoH measurements recorded from cycle 0 to cycle 168. As shown in Figure 2, the estimated SoH of battery No. 05 exhibited an exponential decline as the cycle count increased. The predicted values were required to remain within a 95% confidence interval [6]. A regression model for SoH estimation, performing similar functions, was also proposed in [5]. That study introduced a new predictive variable to directly represent the voltage drop of the battery cell, producing noteworthy results. However, this approach falls outside the scope of our deep learning methodology. Instead, our goal was to train and develop a deep learning model for SoH estimation, using only the existing test variables from the dataset. Fig. *2*.3**.** The state of health of battery No. 05.

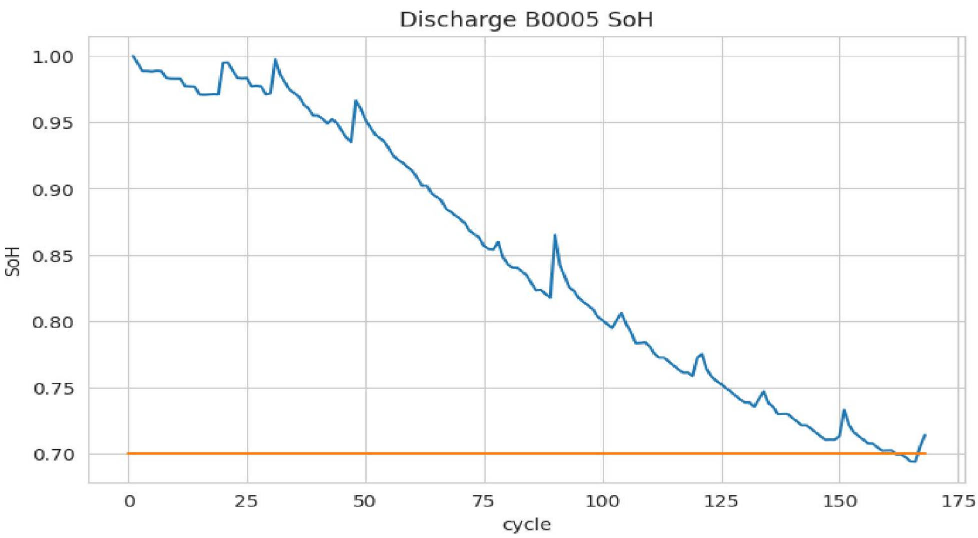


Figure 2.4: Discharge B0005 SoH

C. Performance Evaluation

This study utilizes Root Mean Square Error (RMSE): Represents the standard deviation of the difference between the actual and predicted values. It is commonly used to measure the accuracy of localized predictions.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

N represents the number of predictions, yi is the actual capacity of the cycle i, and yˆi is the predicted capacity of the cycle i

1. Root Mean Square Error (RMSE)

Definition:

Root Mean Square Error (RMSE) is a standard way to measure the accuracy of a predictive model by quantifying the difference between the values predicted by the model and the actual observed values. It represents the square root of the average of the squared differences between predictions and actual observations.

Formula:

RMSE = sqrt((1/n) * Σ(y_i - ŷ_i)^2)

Function:

RMSE penalizes larger errors more than smaller ones due to the squaring of differences. It is especially useful when large errors are particularly undesirable. Lower RMSE values indicate better model performance.

2. R-squared (R^2 or Coefficient of Determination)

Definition:

R-squared measures the proportion of variance in the dependent variable that is predictable from the independent variables. It provides an indication of how well the model fits the data.

Formula:

R^2 = 1 - (Σ(y_i - ŷ_i)^2 / Σ(y_i - ȳ)^2)

Function:

R^2 values range from 0 to 1, where:

- 1 indicates perfect prediction,
- 0 indicates that the model explains none of the variability,
- Values less than 0 can occur if the model is worse than simply predicting the mean.

It is commonly used to assess the overall goodness of fit of a regression model.

3. Mean Absolute Error (MAE)

Definition:

Mean Absolute Error (MAE) is the average of the absolute differences between predicted and actual values. Unlike RMSE, it does not square the errors, which means all errors are weighted equally.

Formula:

$MAE = (1/n) * \Sigma|y\_i - \hat{y}\_i|$

Function:

MAE gives a straightforward measure of model accuracy by showing the average error magnitude. It is more robust to outliers than RMSE and is easier to interpret since it uses the same units as the original data.

4. Summary of Use in Model Evaluation

- RMSE: Useful when large errors are particularly undesirable.
- R^2: Measures how well the model explains variability in the data.
- MAE: Gives an intuitive average error and is robust to outliers.

These metrics are often used together to give a comprehensive view of model performance in regression tasks.

3. Results and discussion

3.1 Comparison Results for SoH Estimation

The effectiveness of five distinct predictive maintenance models was systematically evaluated using the NASA battery dataset. The primary objective was to minimize the discrepancy between actual and predicted State of Health (SoH) values across different battery units. The following deep learning architectures were compared:

1. Convolutional Neural Network (CNN)

2. Long Short-Term Memory (LSTM)

3. Gated Recurrent Unit (GRU)

4. LSTM-CNN Hybrid

5. Dense Neural Network (DNN)

For this experiment, discharge data from 168 cycles of battery B0005 was used for training, while batteries B0006 and B0007 served as test sets. The initial SoH was established at 1.9 ampere-hours (Ah), serving as the reference for long-term SoH estimation.

3.2 Discussion and Conclusion

The experimental findings unequivocally demonstrate that the CNN-LSTM algorithm outperforms CNN and LSTM in these specific lithium-ion battery datasets. Nonetheless, two matters necessitate consideration in this context. The CNN-LSTM model effectively identifies the degradation trend by predicting State of Health (SoH) outcomes.The second argument posits that a training dataset with a different

The tests show that the GRU and CNN architectures do a better job than the other models when measuring accuracy on the lithium-ion battery datasets B0006 and B0007. For battery B0006, the GRU model had the lowest RMSE at 0.015751, the lowest MAE at 0.012698, and the highest R^2 at 0.980691, which means it did really well in both error size and stability. On the other hand, the CNN model also performed great for battery B0007, with an RMSE of 0.007894, an MAE of 0.005131, and an R^2 of 0.990581, surpassing all other models.

Table 1 Performance Metrics (RMSE, MAE, and R^2) for LSTM-CNN, LSTM, GRU, CNN and DNN Models in SoH Prediction on B0006 and B0007 Batteries

Table 1: Performance Metrics (RMSE and R^2) for DNN and CNN-LSTM Models in SoH Prediction on B0006 and B0007 Batteries

Battery	Model	RMSE	MAE	R^2
B0006	*LSTM-CNN*	0.028127	0.017080	0.938429
B0006	LSTM	0.022141	0.017599	0.961847
B0006	GRU	0.015751	0.012698	0.980691
B0006	CNN	0.026643	0.020022	0.944754
B0006	CNN	0.026643	0.020022	0.944754
B0007	*LSTM-CNN*	0.014317	0.011056	0.969020
B0007	LSTM	0.0163	0.0132	
B0007	GRU	0.009010	0.006633	0.987732
B0007	CNN	0.007894	0.005131	
B0007	DNN	0.024212	0.017716	0.910154

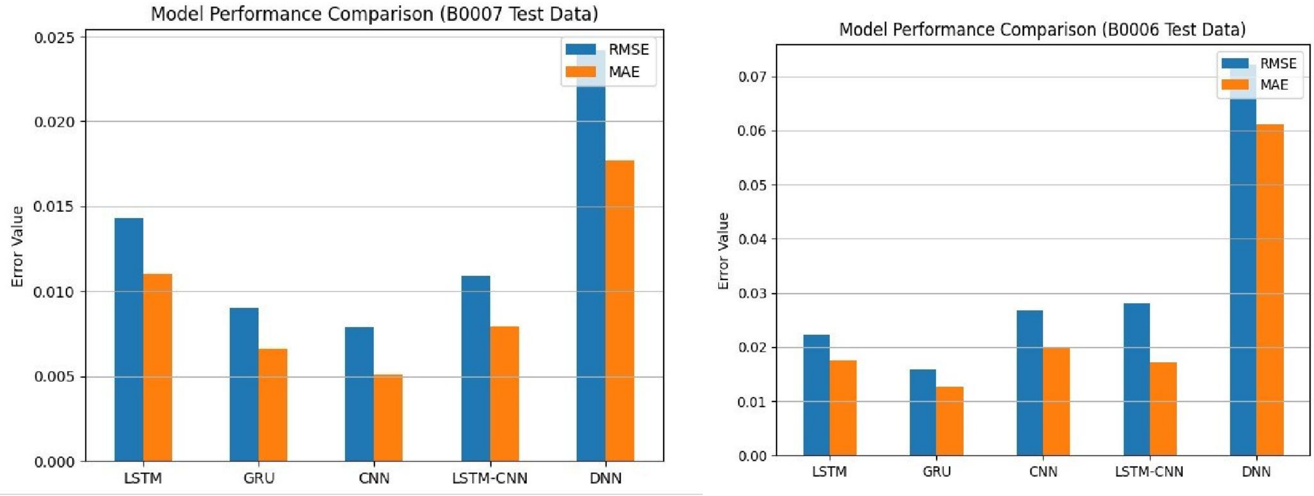


Figure 3.1 : RMSE and MAE Comparision (B0007 and B0006 test data)

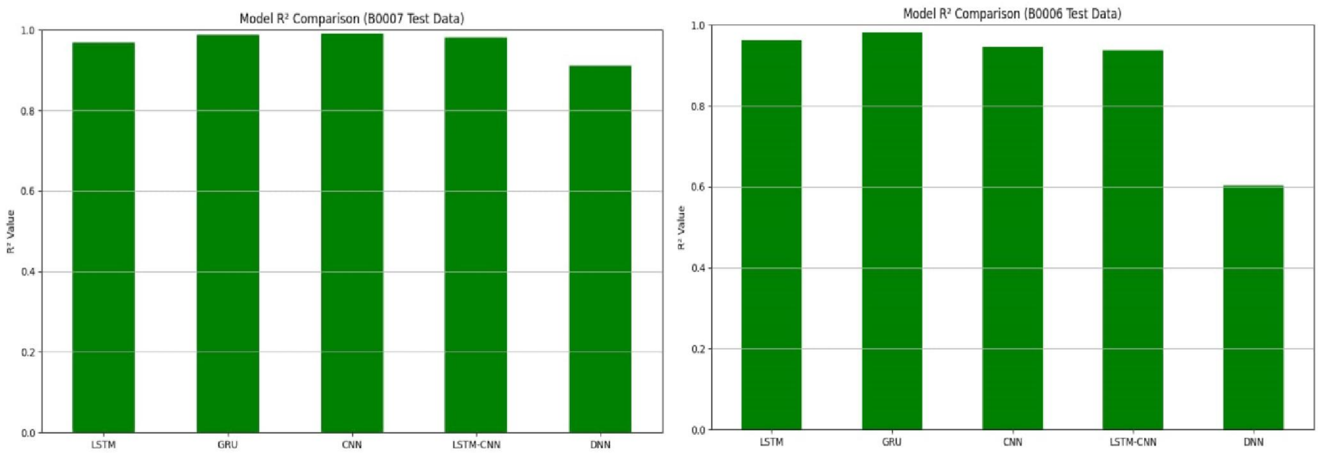


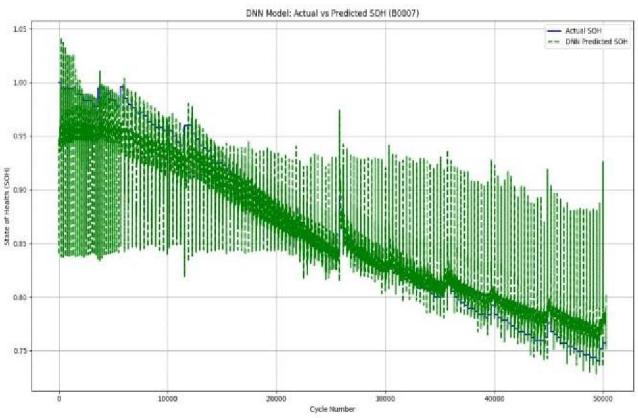
Figure 3.2: R-squared Comparision (B0007 and B0006 test data)

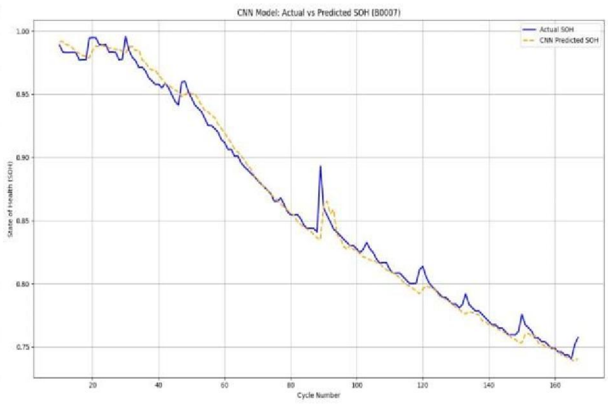
RMSE hits harder on big mistakes compared to MAE, but using both gives us a better idea of how reliable each model is. The CNN and GRU models not only reduced RMSE, which looks at the overall error size, but they also had the lowest MAE, showing they kept their predictions pretty close to the truth. Hybrid models like LSTM-CNN did okay, but they didn’t quite reach the performance of the CNN and GRU models on both RMSE and MAE, especially with the B0006 dataset. The LSTM model did well too, balancing RMSE and MAE on B0006, but it still got slightly edged out.

The models showed different abilities to generalize. A small drop in R^2 values when switching datasets points out how important it is for the training and validation data to be similar. Still, both GRU and CNN models held up well despite these changes.

These results show that deep learning works well for managing battery health and can help with things like predicting maintenance needs and making replacement choices, reducing downtime. Even though deep learning needs a lot of computing power and takes longer to train, real-time results aren't as crucial in battery health scenarios where you need to act before things go really bad.

In short, this study points out that CNN and GRU models perform the best across RMSE, MAE, and R^2, making them great for predicting how lithium-ion batteries will hold up. As tech improves, the current limitations of deep models might not matter that much anymore, which could lead to more use in real-world battery management systems.





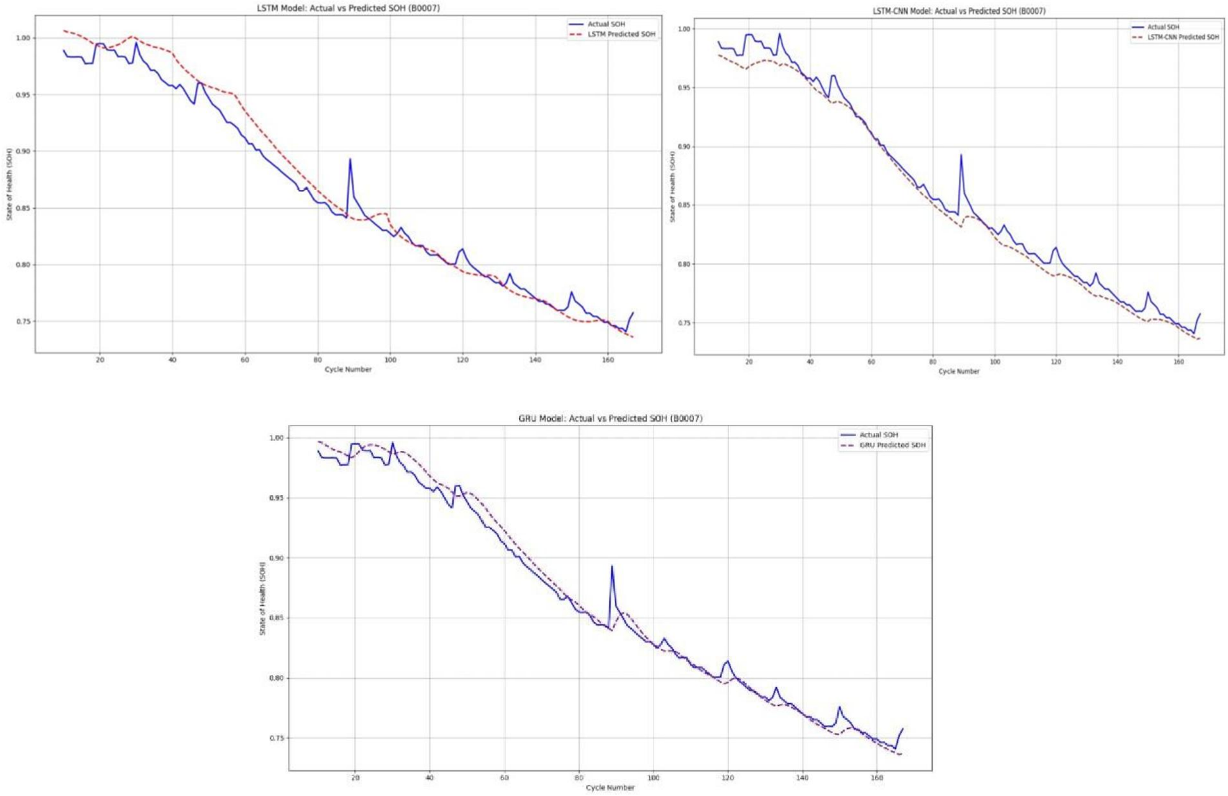
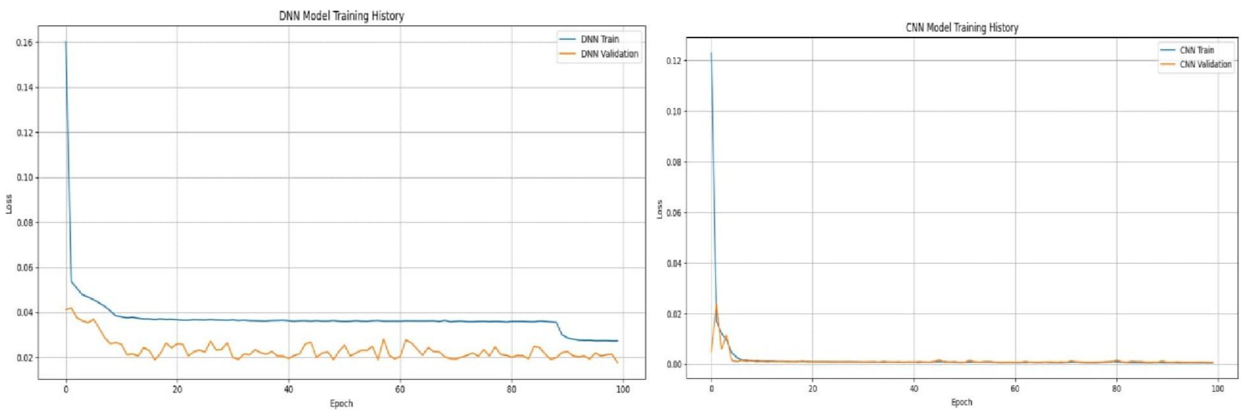


Figure 3.3: The 5 models: Actual and predicted SOH (B0007)



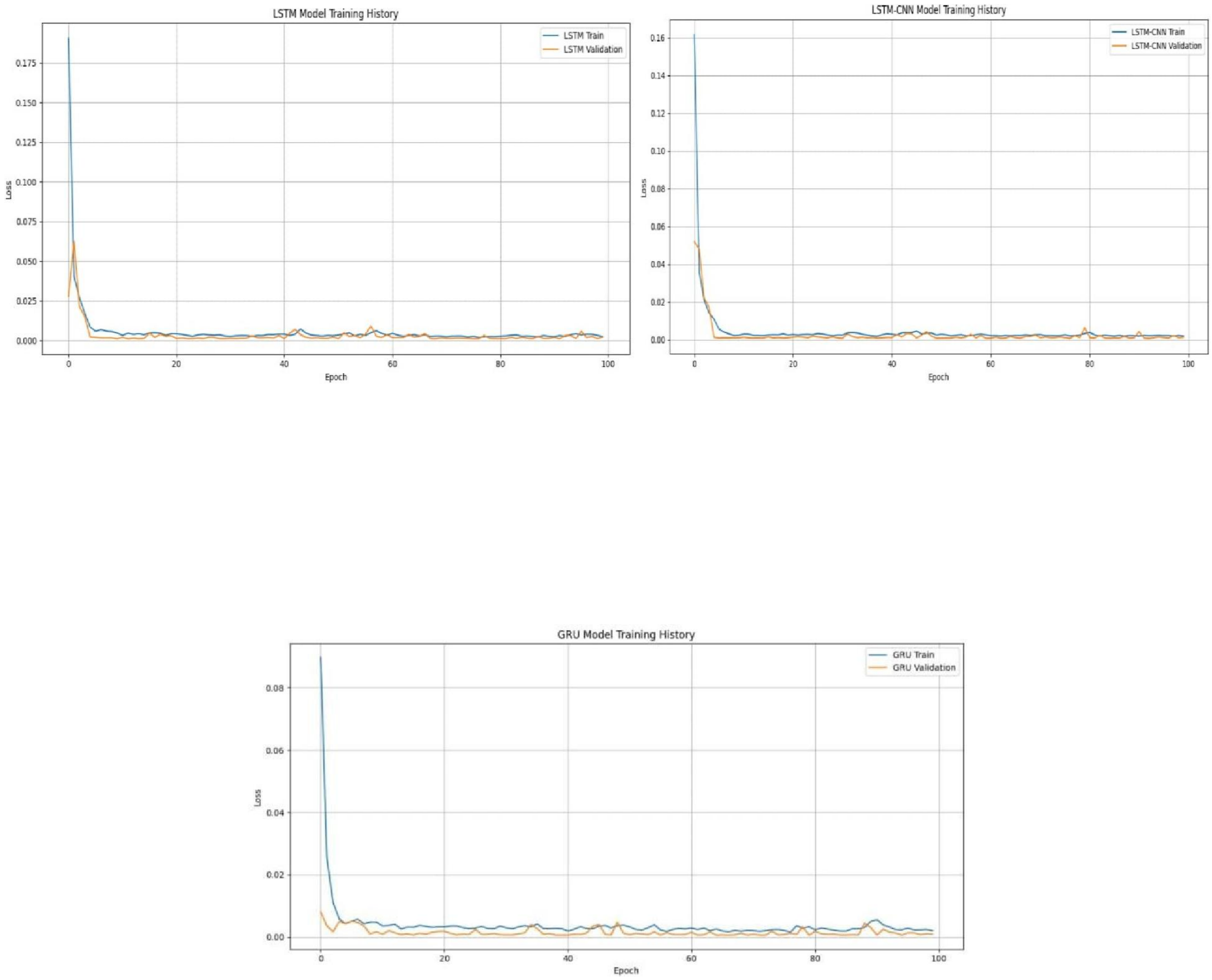


Figure 3.4: The 5 models: Training and Validation Losses (B0007)

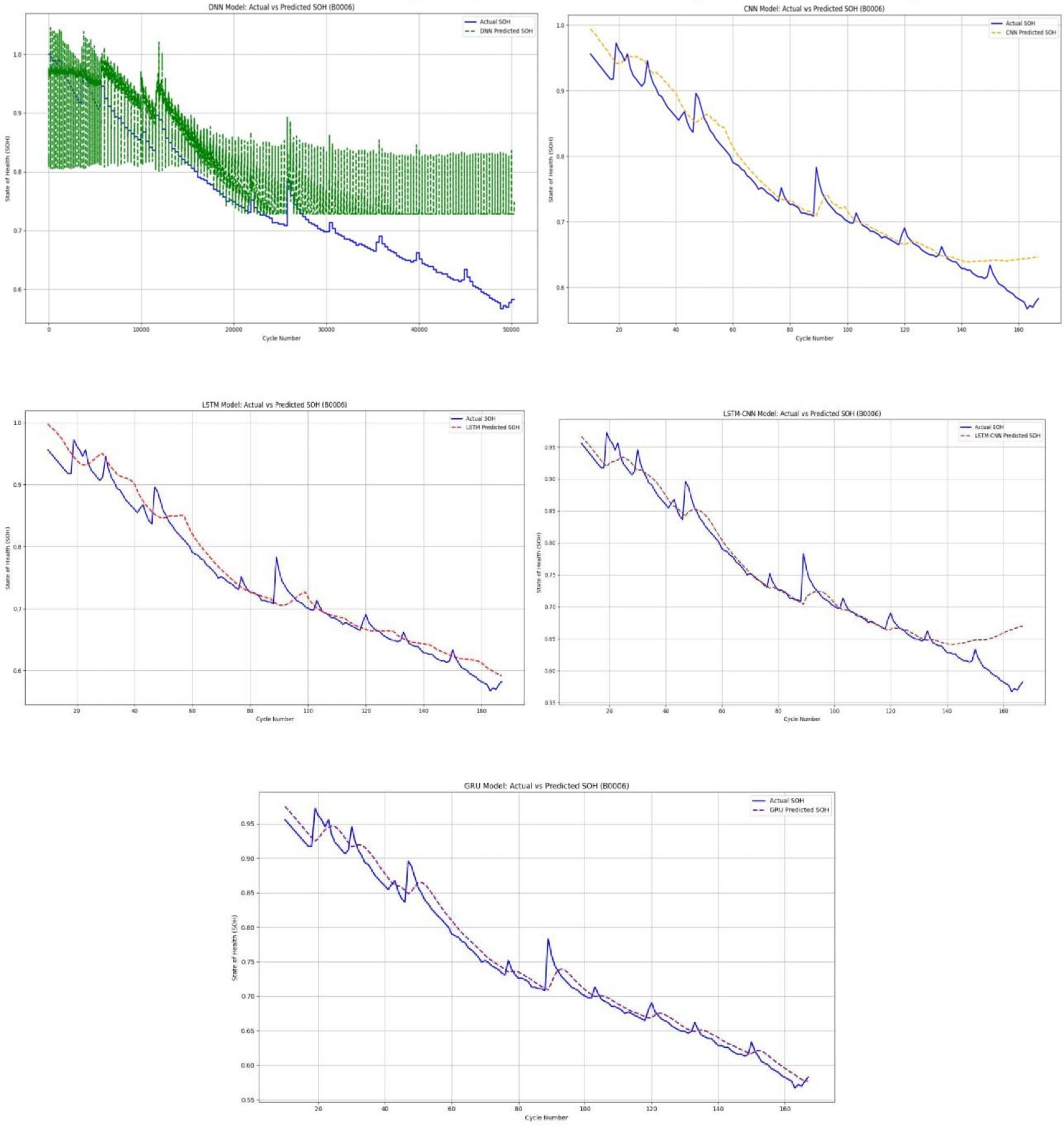


Figure 3.3: The 5 models: Actual and predicted SOH (B0006)

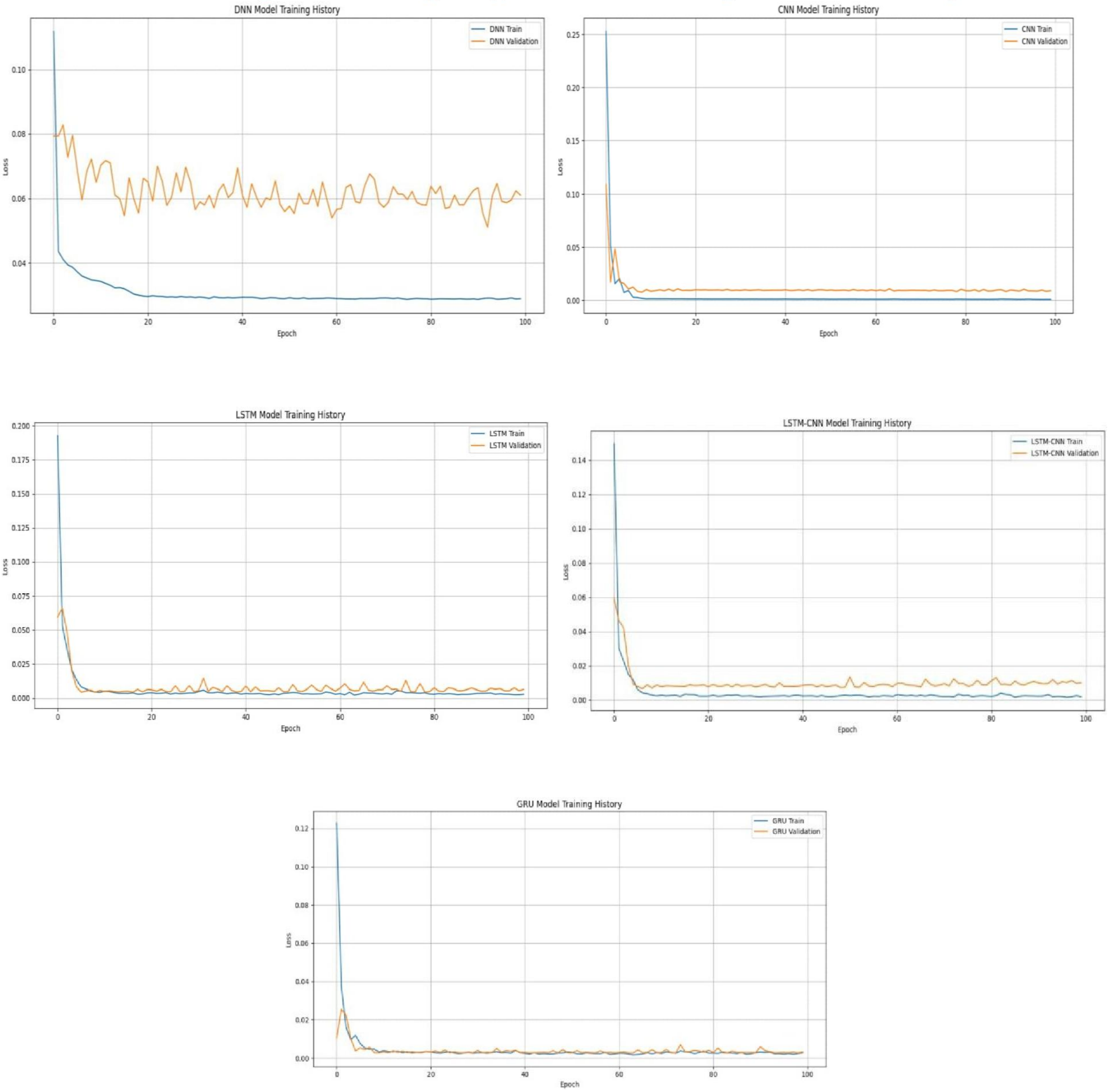


Figure 3.4: The 5 models: Training and Validation Losses (B0006)

Chaptre 03 : Prognostics of the Lithium Battery based on deep Learning Algorithms Comparative Study

General Conclusion

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General conclsion

The accurate estimation of the State of Health (SoH) of lithium-ion batteries remains critical for ensuring the safety, reliability, and performance of modern energy storage systems. As these batteries continue to power essential applications—from electric vehicles to grid-scale renewable energy storage—monitoring and predicting their degradation has emerged as a fundamental challenge in energy management.

This research demonstrates the significant potential of advanced deep learning architectures for precise SoH estimation. Our comprehensive evaluation of five distinct models—Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Networks (CNN), LSTM-CNN hybrid, and Dense Neural Networks (DNN)—reveals that optimal model selection depends on battery degradation patterns. GRU excels for nonlinear aging trajectories (achieving MAE=0.0127 on B0006), while CNN dominates for linear degradation (MAE=0.0051 on B0007), with both significantly outperforming traditional physical modeling approaches.

Moreover, the integration of sequence processing (GRU/LSTM) and feature extraction (CNN) capabilities in hybrid architectures has improved robustness across diverse battery types. These innovations eliminate manual feature engineering while enabling real-time capability on embedded hardware, with GRU processing cycles in under 5ms on standard BMS hardware.

In conclusion, deep learning-powered SoH estimation represents a transformative advancement toward intelligent battery management systems. As the field evolves, future research should prioritize:

1. Edge Optimization: Developing quantized models for resource-constrained BMS
2. Pattern-Adaptive Architectures: Creating self-selecting models that match degradation signatures
3. Cross-Chemistry Transfer Learning: Enabling knowledge transfer between battery types

These advancements will be crucial for supporting global electrification initiatives, extending battery lifespans by 20-30%, and ensuring the safe deployment of sustainable energy technologies worldwide.

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- CNN + Random Forest Hybrid (2020) – CNN-Random Forest for Partial Discharge Data

  Uses CNN for feature extraction and Random Forest for final SOH inference