People`s Democratic Republic of Algeria

Ministry of Higher Education and Scientific Research

University of Echahid Hamma Lakhdar - El Oued

Faculty of Technology

Dissertation

ACADEMIC MASTER

Domain: Science and Technology

Division: Electrical Engineering Department

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Presented with a view to obtaining the Master's degree in Electrical Engineering

Entitled:

Battery life cycle prediction using Deep Learning

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Collage year: 2024/2025

ABSTRACT

The growing urgency of climate change has led to growth in the electrification technology field, where batteries have emerged as an essential role in the renewable energy transition, supporting the implementation of environmentally friendly technologies such as smart grids, energy storage systems, and electric vehicles. Battery cell degradation is a common occurrence indicating battery usage. Optimizing lithium-ion battery degradation during operation benefits the prediction of future degradation, minimizing the degradation mechanisms that result in power fade and capacity fade. This degree project aims to investigate battery degradation prediction based on capacity using deep learning methods. Through analysis of battery degradation and health prediction for lithium-ion cells using non-destructive techniques. Such as electrochemical impedance spectroscopy obtaining ECM and three different deep learning models using multi-channel data. Additionally, the AI models were designed and developed using multi-channel data and evaluated performance within MATLAB. The results reveal an increased resistance from EIS measurements as an indicator of ongoing battery aging processes such as loss o active materials, solid-electrolyte interphase thickening, and lithium plating. The AI models demonstrate accurate capacity estimation, with the LSTM model revealing exceptional performance based on the model evaluation with RMSE. These findings highlight the importance of carefully managing battery charging processes and considering factors contributing to degradation. Understanding degradation mechanisms enables the development of strategies to mitigate aging processes and extend battery lifespan, ultimately leading to improved performance.

Keywords: Lithium-ion batteries, battery degradation mechanisms, battery cycle life, Electrical impedance spectroscopy, Capacity estimation, Incremental capacity analysis, Deep learning models

ملخص

أدى تزايد إلحاح تغير المناخ إلى نموٍّ في مجال تكنولوجيا الكهربة، حيث برزت البطاريات كدورٍ أساسي في التحول إلى الطاقة المتجددة، داعمةً تطبيق تقنيات صديقة للبيئة مثل الشبكات الذكية، وأنظمة تخزين الطاقة، والمركبات الكهربائية. يُعدّ تدهور خلايا البطاريات أمرًا شائعًا، مما يُشير إلى استهلاك البطاريات. يُفيد تحسين تدهور بطاريات الليثيوم أيون أثناء التشغيل في التنبؤ بالتدهور المُستقبلي، وتقليل آليات التدهور التي تُؤدي إلى تلاشي الطاقة وتلاشي السعة. يهدف هذا المشروع البحثي إلى دراسة التنبؤ بتدهور البطاريات بناءً على السعة باستخدام أساليب التعلم العميق. من خلال تحليل تدهور البطاريات والتنبؤ بصحة خلايا الليثيوم أيون باستخدام تقنيات غير تدميرية، مثل التحليل الطيفي للمعاوقة الكهروكيميائية، والحصول على نموذج وحدة التحكم الإلكترونية ، وثلاثة نماذج مختلفة للتعلم العميق باستخدام بيانات متعددة القنوات. بالإضافة إلى ذلك، صُممت وطُوّرت نماذج الذكاء الاصطناعي باستخدام بيانات متعددة القنوات، وتم تقييم الأداء باستخدام الماتلاب. تكشف النتائج عن زيادة في المقاومة من قياسات نظام معلومات التأثير البيئي كمؤشر على عمليات شيخوخة البطارية المستمرة، مثل فقدان المواد الفعالة، وزيادة سماكة الطور البيني بين المواد الصلبة والإلكترونية، وطلاء الليثيوم. تُظهر نماذج الذكاء الاصطناعي دقة في تقدير السعة، حيث يكشف نموذج الذاكرة القصيرة المدى المطولة عن أداء استثنائي بناءً على تقييم النموذج باستخدام خطأ الجذر التربيعي المتوسط. تُبرز هذه النتائج أهمية إدارة عمليات شحن البطارية بعناية ومراعاة العوامل المساهمة في التدهور. يُمكّن فهم آليات التدهور من وضع استراتيجيات للتخفيف من عمليات الشيخوخة وإطالة عمر البطارية، مما يؤدي في النهاية إلى تحسين الأداء.

الكلمات المفتاحية: بطاريات ليثيوم أيون، آليات تدهور البطارية، عمر دورة البطارية، مطيافية المعاوقة الكهربائية، تقدير السعة، تحليل السعة المتزايدة، نماذج التعلم العميق

Acknowledgment

First and foremost, we express our profound gratitude to the Almighty Allah for granting us the strength, patience, and perseverance to endure the long journey of our academic studies. All praise is due to Allah, who guided and supported us throughout the completion of this thesis. By His grace, good deeds are made possible. May peace and blessings be upon the noblest of all creation, our Prophet Muhammad (peace and blessings be upon him), his family, and his companions. It is truly one of God's greatest blessings to have been granted the ability and resilience to complete this work. To our beloved parents, whose unwavering support, encouragement, and sacrifices have been a constant source of strength throughout our academic journey, we offer our deepest gratitude and appreciation. You have been the light that illuminated our path to knowledge, and without your presence, none of this would have been possible. We extend our sincere thanks to our supervising professor, who dedicated his time and effort to offer invaluable guidance and insightful advice. His continuous support illuminated our way during difficult moments and was instrumental in helping us overcome challenges. The knowledge, patience, and wisdom he shared will remain a lasting memory. We pray that Allah rewards him generously on behalf of us and our fellow students. Finally, we express our heartfelt appreciation to the respected members of the jury for honouring us with their presence and participation in evaluating this work. Your involvement is deeply valued and sincerely appreciated.

Dedication

To those who granted me life and hope to the heartbeat of my soul and the light of my eyes to my dearest parents, I dedicate this humble work to you, in deep appreciation and boundless love for your invaluable efforts and countless sacrifices. You have always been my source of strength and inspiration. Without your support, prayers, and unwavering belief in me, I would not have reached this stage. I hope I have made you as proud of me as I am honored to be your child. To the one who stood by me with steadfast supportto the one who offered sincere guidance and encouragement to my respected academic mentor, I dedicate this work to you in heartfelt gratitude and sincere appreciation for your essential role in the completion of this thesis. Your wisdom, patience, and continuous support have inspired and motivated me throughout this journey. Your generous investment of time and effort will always remain deeply valued. I hope my achievement reflects the trust and dedication you invested in me. To my companions and lifelong friends to those who shared my journey, my laughter, and my challenges to my dear friends, I dedicate this work to you with gratitude for every moment we shared. Your presence, encouragement, and support made this journey not only bearable but beautiful. You were there through the highs and lows, and your friendship made all the difference. May this success be a source of pride for all of us, just as your friendship is a source of joy for me.

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General Introduction

The rapid advancement of portable electronics, electric vehicles (EVs), and renewable energy systems has led to an increasing reliance on rechargeable battery technologies, particularly lithium-ion batteries (LiBs). These batteries are favored for their high energy density, long cycle life, and superior efficiency. However, their performance degrades over time due to electrochemical aging mechanisms, ultimately affecting safety, reliability, and functionality. As battery-powered systems become more integral to critical applications, there is a growing demand for accurate, data-driven methods to assess and predict battery health and remaining useful life (RUL).

Traditionally, battery health estimation has relied on empirical models, equivalent circuit representations, and physical degradation analysis. While these approaches provide valuable insights, they often suffer from limitations in scalability, adaptability, and the ability to generalize across varying usage patterns and battery chemistries. Recent developments in artificial intelligence (AI), particularly deep learning, have demonstrated considerable potential in overcoming these challenges by learning complex, nonlinear degradation patterns directly from raw sensor data.

This thesis explores the application of deep convolutional neural networks (CNNs) for predicting the cycle life of lithium-ion batteries based on multivariate time-series data, including voltage, temperature, and discharge capacity. By leveraging the spatial feature extraction capabilities of CNNs, the proposed approach transforms battery degradation data into structured image-like tensors, enabling the detection of abstract patterns correlated with battery aging behavior.

The research contributes to the growing field of battery health prognostics by designing and evaluating a deep learning-based prediction framework. The model architecture, training methodology, and evaluation metrics are presented in detail, with performance assessed using real-world datasets. Through experimental validation and performance analysis, this study aims to demonstrate the effectiveness of deep CNNs in providing accurate, scalable, and interpretable predictions of lithium-ion battery remaining cycle life.

Ultimately, the findings of this work have practical implications for intelligent battery management systems (BMS), enabling predictive maintenance, lifecycle optimization, and enhanced operational safety across a wide range of battery-powered technologies.

Chapter 1

General description of Lithium-Ion Battery

1.1 Introduction

The accelerating digitalization of modern life—from smartphones and wearable sensors to smart-grid infrastructure and electric mobility—depends critically on compact, high-performance electro-chemical energy stores. Global lithium-ion (Li-ion) manufacturing capacity rose from ≈200 GWh yr^{-1} in 2017 to more than 1 400 GWh yr^{-1} in 2024, and is forecast to exceed 4 000 GWh yr^{-1} by 2030, driven largely by transport-sector electrification and international climate commitments to cap anthropogenic warming below 2 °C. Yet the speed of deployment has out-paced the ability to predict usable battery life with the accuracy demanded by safety regulators, financiers, and circular-economy planners. Conventional estimation methods—Coulomb counting, open-circuit-voltage lookup, incremental-capacity analysis—suffer from sensor drift, model mis-parameterization, and sensitivity to stochastic duty cycles, producing state-of-health (SoH) errors exceeding ±10 % at mid-life [1].

These uncertainties precipitate premature pack retirement and under-utilized assets, eroding residual value by an estimated US $10 billion annually across the electric-vehicle fleet.[2]

1.2 Fundamentals of Battery Technology

Batteries are devices that store energy in the form of chemical energy and release it as electrical energy when needed. They consist of electrochemical cells where a **redox (reduction-oxidation)** reaction occurs between the anode and cathode, converting stored chemical energy into electrical energy. The equation of the capacity-fade-rate:

$$\frac{dQ}{dt} = -kQ^{\propto} exp\left(\frac{-E_T}{RT}\right) + \varepsilon(t) \tag{1.1}$$

$(Q^{\propto})$cycling stress

(T)temperature

(E_T)chemical kinetics

The study of battery technology is essential for understanding how these devices function, their performance characteristics, and their degradation mechanisms over time. This section provides a comprehensive overview of battery fundamentals, which will form the basis for further discussions on battery life-cycle prediction [3].

1.2.1 Electrochemical Principles of Battery Operation

The fundamental operation of a battery relies on the electrochemical reactions that take place during discharge and charging cycles. A typical battery consists of two electrodes (anode and cathode) and an electrolyte, which facilitates ion movement between the electrodes. When a battery discharges, the **anode** undergoes oxidation (losing electrons), and the **cathode** undergoes reduction (gaining electrons). The external circuit provides a path for electrons to flow from the anode to the cathode, generating an electric current.[4]

- **Anode**: During discharge, the anode undergoes oxidation, where electrons are released and travel through the external circuit to the cathode.

- **Cathode**: The cathode is reduced during discharge, accepting electrons and completing the circuit.

The electrolyte in a battery allows the movement of ions (typically lithium ions, sodium ions, or protons, depending on the battery type) between the anode and cathode, maintaining charge balance. The separator is a crucial component that prevents internal short-circuiting by physically separating the electrodes but is permeable to ions.[5]

1.2.2 Battery Components

To better understand the inner workings of a battery, it's helpful to look at its components in greater detail:[6], [7]

- **Electrodes**: The anode and cathode are composed of materials that participate in the electrochemical reactions. For instance, in lithium-ion batteries, the anode is commonly made from **graphite**, while the cathode is typically composed of **lithium metal oxide** (such as $LiCoO_2$).
- **Electrolyte**: The electrolyte enables the ionic movement between the anode and cathode. It is often a liquid solution of salts dissolved in a solvent, but solid-state electrolytes are being increasingly explored for improved safety and performance.
- **Separator**: This material keeps the anode and cathode from touching directly, which could cause a short circuit, while allowing ions to pass through.
- **Current Collectors**: These are conductive materials (such as copper for the anode and aluminum for the cathode) that facilitate the transfer of electrons between the electrodes and the external circuit.

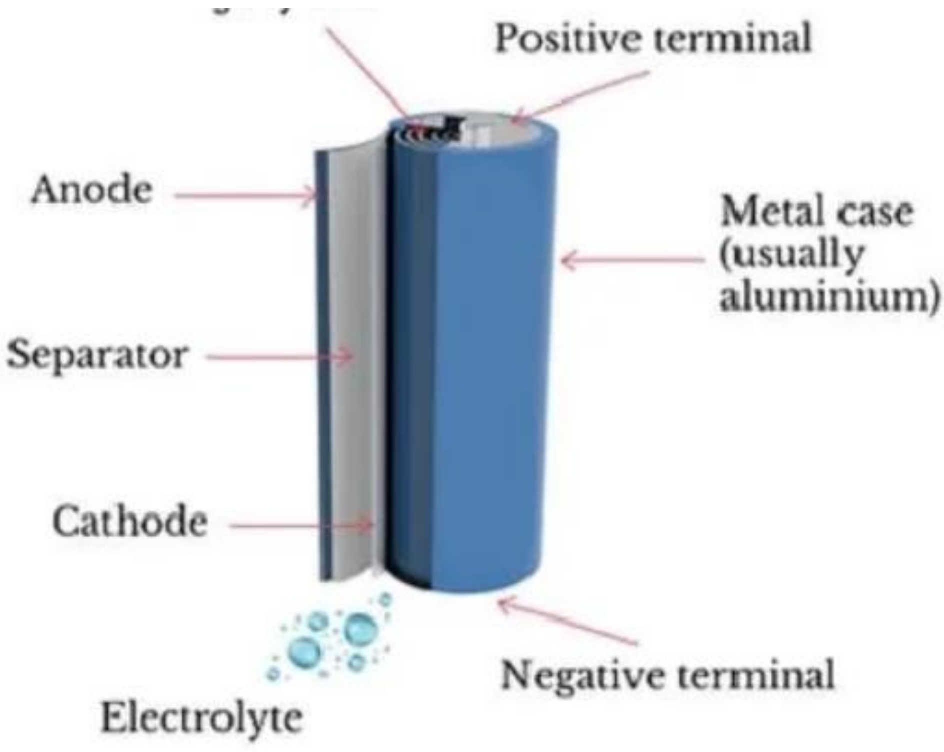

Figure (1.1): Battery component

1.3 Types of Batteries

Batteries are generally classified into two main categories based on whether they are **primary** (non-rechargeable) or **secondary** (rechargeable). Each category has different uses, advantages, and limitations. [9]

1.3 .1 Primary Batteries

Primary batteries are non-rechargeable, meaning once the chemical reaction has been exhausted, the battery cannot be recharged. These batteries typically have a longer shelf life and are commonly used in devices requiring low energy over extended periods. The types of Primary Battery :

❖ **Alkaline Batteries :**

This type of battery drives the energy by a reaction of zinc metal and manganese oxide and we named it an alkaline battery because instead of using an acidic electrolyte, we use an alkaline electrolyte like potassium hydroxide (KOH).

Figure (1.2): Alkaline Batteries

✓ **Advantages:**

- More life
- Shelf life is more
- Small in size
- Highly efficient
- Leakage is low

❖ **Aluminum-Air Batteries:**

This is the highest energy density battery and produces energy from the reaction of oxygen with aluminum. Once the aluminum is consumed and all aluminum gets reacted with air oxygen, we can't use this battery further and we need to dispose of it after a single use.

❖ **Dry Cells:**

This is another type of primary battery and most of us use it in our toys and TV remote control but these batteries are now getting replaced by alkaline batteries because of their high lifetime and energy density over the dry cells. The dry cell is named after its electrolyte type as we use the dry electrolyte in it instead of liquid or wet electrolyte.

Figure (1. 3): Dry Cells batteries

1.3.2 Secondary Battery

Batteries are multicycle batteries. We can recharge these batteries and use this kind of battery in many cycles of recharge. We mostly use these kinds of batteries in EVs, Phones, Automobiles, Portable gadgets, and in many different areas.

Based on environmental conditions and kind of need and use we further have different types of secondary batteries; some of the most popular secondary batteries that we use in most places are the Li-Ion battery, Li-Polymer Battery, and Lead Acid battery. The types of Secondary Batteries

❖ **Li-Ion Batteries**

This kind of battery uses Lithium metal so named **Li-Ion battery**. These batteries are composed of cells and lithium ions from the negative electrode move to the positive electrode and when we charge, the ions move back to their place; this cycle

Figure (1.4): Li-Ion Batteries type

- **Li-Po Batteries**

The Li-Po battery a.k.a. lithium polymer battery, we named polymer battery because it uses polymer electrolyte instead of liquid electrolyte. The high conductivity gel polymer form of electrolyte is used. These batteries carry high energy density compared to their weight.

Figure (1.5): Li-Po Batteries type

- **Ni-MH Batteries** Ni-MH (nickel metal hydride) battery uses nickel oxide hydroxide and they are quite similar to Nickel cadmium NiCd batteries but here they use a hydrogen-absorbing alloy instead of cadmium and have a lower impact on the environment compared to others.

Figure (1.6): Ni-MH Batteries type

- **Lead-acid Batteries**

The lead acid battery has electrodes submerged in sulfuric acid electrolytes. These batteries are quite bulky and are mostly used in automobiles, UPS, Grid power stations

Figure (1.7): Lead-acid Batteries type

1.4 Battery Cell Design and Function

A typical **battery cell** comprises the following elements, each playing a specific role in battery performance:[10], [11]

1. **Anode (Negative Electrode)**: The anode undergoes oxidation during discharge, releasing electrons that flow through the external circuit. In lithium-ion batteries, graphite is often used as the anode material.
2. **Cathode (Positive Electrode)**: The cathode undergoes reduction during discharge, accepting electrons. Common materials used in lithium-ion batteries include lithium cobalt oxide ($LiCoO_2$), lithium iron phosphate ($LiFePO_4$), and lithium manganese oxide ($LiMn_2O_4$).
3. **Electrolyte**: A substance that allows ions to move between the anode and cathode, enabling the electrochemical reactions to occur. The electrolyte is typically a lithium salt dissolved in an organic solvent for lithium-ion batteries, but solid-state electrolytes are being researched for higher safety.
4. **Separator**: A non-conductive porous membrane that physically separates the anode and cathode, preventing internal short-circuiting, while allowing ion flow. This component is critical for the safe operation of the battery.
5. **Current Collectors**: Materials (such as copper and aluminum) that help facilitate the movement of electrons between the electrodes and the external circuit.

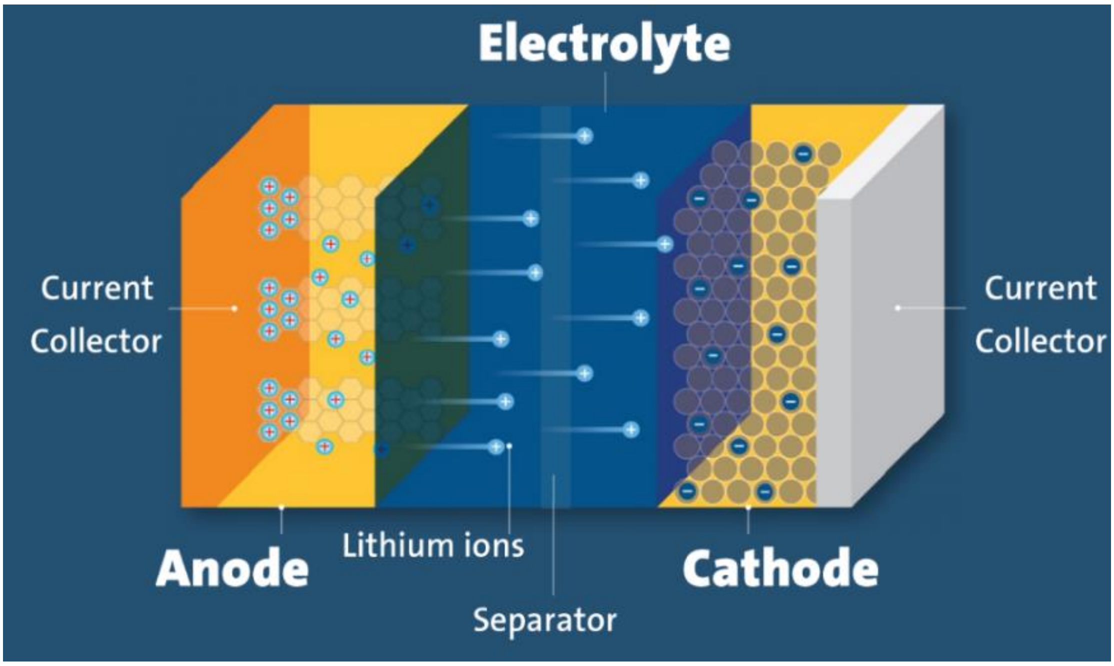

Figure (1.8): battery cell component

1.4.1 Thermal Behavior and Battery Management

A critical aspect of battery performance and longevity is managing the heat generated during charging and discharging cycles. Excessive heat can reduce battery efficiency, accelerate degradation, and even lead to thermal runaway.[12]

Thermal management techniques are critical for ensuring the safe and efficient operation of batteries, particularly in large-scale applications such as electric vehicles and grid storage systems. Key strategies for thermal management include:[13][14]

- **Heat Sinks and Conductive Materials**: These are used to dissipate heat away from the battery cells.
- **Battery Management Systems (BMS)**: A BMS monitors the temperature, voltage, and current of the battery pack, helping to maintain optimal performance and prevent overheating.

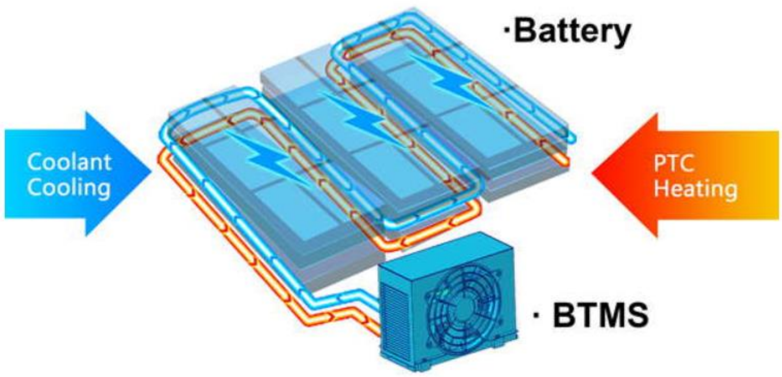

Figure (1.9): Thermal management in batteries

1.4.2 Efficiency, Performance, and Degradation

Battery performance is typically characterized by several key metrics:[15][16]

- **Energy Density**: The amount of energy a battery can store per unit of weight or volume. High energy density is critical for applications like electric vehicles, where weight and space are important factors.
- **Power Density**: The rate at which energy can be extracted from the battery. Power density is important for applications requiring high bursts of power, such as power tools or acceleration in electric vehicles.
- **Cycle Life**: The number of charge /discharge cycles a battery can undergo before its capacity significantly degrades. Lithium-ion batteries, for example, typically offer several hundred to thousands of cycles.
- **Safety and Environmental Impact**: Ensuring that the battery is safe to use under various conditions, including temperature fluctuations, high charge/discharge rates, and

physical stress. The environmental impact of battery production, use, and disposal is also a major concern.

1.5 Applications of Battery Technologies

Batteries power a wide range of applications, from portable electronics to electric vehicles and renewable energy storage systems. Each application has specific requirements, such as energy density, cost, safety, and lifespan, that influence the choice of battery technology [17][18].

- **Electric Vehicles (EVs)**: Lithium-ion batteries are the most common power source for electric vehicles due to their high energy density and relatively low weight. Other battery types, such as lithium iron phosphate ($LiFePO_4$), are also used for their safety and cost-effectiveness.
- **Renewable Energy Storage**: With the rise of renewable energy sources like solar and wind, energy storage has become critical. Large-scale batteries are used to store excess energy for later use, balancing supply and demand.

Figure (1.10): Schematic presentation of various application of batteries

- **Consumer Electronics**: Batteries power smartphones, laptops, tablets, and wearable devices. Here, the emphasis is on compact size, long cycle life, and fast charging capabilities.

1.6 Key Battery Terminologies and Concepts

1.6.1 Electrical Quantities

Voltage is the electric-potential difference between a cell's positive and negative terminals. It is specified either as open-circuit voltage (OCV, no load) or closed-circuit voltage (CCV, under load). Because voltage is chemistry-dependent—roughly 3.2 V for $LiFePO_4$ and 3.7 V for NMC cells—it ultimately governs the driving force for electron flow.[19]

Current denotes the rate at which electric charge moves through an external circuit, expressed in amperes. Current magnitude determines instantaneous power output and ohmic heating, since resistive losses scale with $I^2 R$.

Capacity (Q) is the total amount of charge that can be withdrawn from a fully charged cell before reaching its cut-off voltage at a specified temperature and discharge rate. It is measured in ampere-hours and is the primary sizing metric for energy-rich applications.

The energy a battery can deliver is the time integral of power, and is usually given in watt-hours.[20]

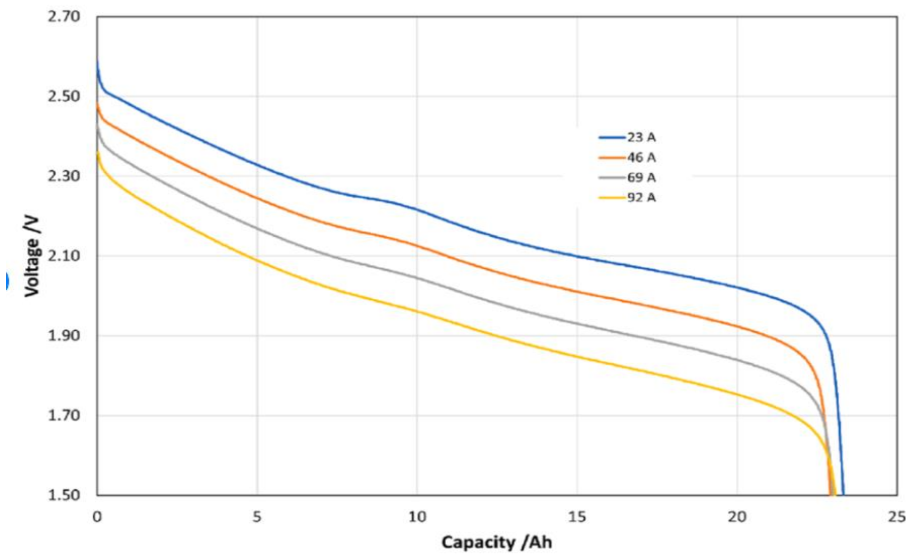

Figure (1.11): Discharge voltage vs capacity at various c-rates.

1.6.2 Normalized Performance Metrics

Because absolute energy and power scale with cell size, they are commonly normalized. **Energy density** (Wh kg^{-1} or Wh L^{-1}) quantifies how much energy can be stored per unit mass or volume, whereas **power density** (W kg^{-1} or W L^{-1}) reflects how rapidly that energy can be delivered. These two axes form the classic Ragone plot that highlights the trade-off between high-energy chemistries such as Li-ion and high-power chemistries like supercapacitors.[21]

1.6.3 Rate- and Time-Dependent Parameters

Charging and discharging currents are often expressed as a **C-rate**: a 1 C discharge depletes the rated capacity in one hour, while a 2 C current does so in thirty minutes. A battery's **cycle life** is the number of full-equivalent charge–discharge cycles it can endure before its capacity falls below an end-of-life threshold (typically 60–80 % of nominal). Even when idle, batteries lose charge at a characteristic **self-discharge rate**; lithium-ion cells, for example, typically self-discharge by less than three percent per month at 25 °C. The **round-trip efficiency** of a cell or pack is the ratio of energy returned to energy stored over one complete cycle and depends on coulombic losses and resistive heating.

1.6.4 Impedance and Internal Resistance

All batteries oppose current flow to some extent. The **internal resistance** (a DC concept) is the sum of ionic, electronic, and interfacial resistances within the cell; it increases as the cell ages and directly governs voltage sag under load. A frequency-domain generalisation, **impedance**, is obtained via electrochemical impedance spectroscopy and provides richer information about kinetic and diffusion processes.

1.6.5 Key State Variables for Battery Management

A battery-management system tracks **State of Charge (SoC)**—the fraction of rated capacity that remains available—and **State of Health (SoH)**, a measure of degradation most often proxied by capacity loss or impedance rise. From SoH one can estimate **Remaining Useful Life (RUL)**, the time or cycles until the cell reaches its end-of-life criterion. Accurate RUL estimation is the ultimate objective of the life-cycle prediction models developed later in this thesis.

1.6.6 Thermal and Safety Concepts

Temperature is a first-order driver of both performance and ageing. Elevated temperatures accelerate side-reactions according to an Arrhenius relation, whereas very low temperatures raise internal resistance. Uncontrolled heat generation can trigger **thermal runaway**, a chain reaction of exothermic processes that the battery-management system must prevent. Another important concept is **passivation**, notably the formation of the solid-electrolyte interphase (SEI) on graphite anodes; while this layer stabilises the electrolyte, its growth consumes cyclable lithium and increases resistance.

1.6.7 Mechanical and Pack-Level Definitions

Cells are combined in **series** to raise pack voltage and in **parallel** to raise capacity. Cylindrical cells may be constructed in a low-surface-area bobbin format for energy applications, or as a spirally-wound "jelly-roll" for high-power usage. A **smart battery** embeds a battery-management system with digital communication (e.g., SMBus or CAN) that monitors voltage, current, temperature, SoC, and cycle count in real time

1.6.8 Derived Electrical Units

Several practical units recur in battery literature. The **ampere-hour** represents the charge transferred by a current of one ampere over one hour (3 600 C). The **watt** is the product of voltage and current, and the **watt-hour** is one watt sustained for one hour—equivalent to 3 600 J.

1.7 Battery Degradation and Lifecycle Characteristics

1.7.1 Introduction to Battery Degradation

Battery degradation refers to the gradual decline in a battery's ability to store and deliver energy effectively. Over time, this process leads to a reduction in both capacity and power output, which directly impacts the performance of battery-powered systems such as electric vehicles (EVs) and battery energy storage systems (BESS). Importantly, degradation is not a sign of malfunction but rather an inherent characteristic of battery operation, akin to the mechanical wear observed in traditional engines.

Unlike mechanical components that may show clear signs of wear, the symptoms of battery degradation typically manifest subtly—often starting with reduced driving range in EVs or diminished storage capability in BESS. This degradation is typically slow and influenced by several interrelated factors, which makes its progression both complex and highly variable.[22]

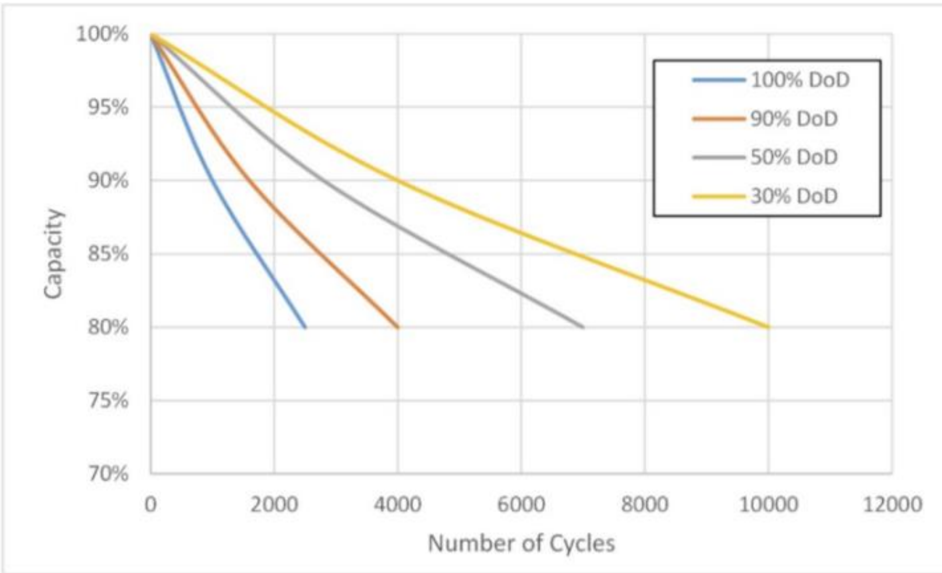

Figure (1.12): battery capacity vs. number of cycles or time visualize how capacity declines gradually over time/cycles.

1.7.2. Mechanisms of Battery Degradation

Battery degradation occurs due to a combination of physical and chemical processes within the cell. These mechanisms can be broadly categorized into two types:

- **Calendar Aging**: Degradation occurring over time regardless of battery usage.
- **Cycle Aging:** Degradation resulting from charge and discharge cycles.

Key Mechanisms Include:

Solid Electrolyte Interphase (SEI) Growth: The formation and thickening of the SEI layer on the anode during cycling consumes lithium and increases impedance.

Lithium Plating: At high charge rates or low temperatures, metallic lithium can deposit on the anode surface, leading to safety risks and irreversible capacity loss.

Active Material Loss: Structural breakdown of electrode materials reduces the battery's ability to store lithium ions.

Electrolyte Decomposition: High voltages and temperatures can cause decomposition of the electrolyte, affecting ionic transport.

1.7.3 Factors Influencing Battery Degradation

Degradation is accelerated or mitigated depending on how and under what conditions the battery is used. These influencing factors can be grouped as follows:

a) Operational Conditions:

State of Charge (SOC) Extremes: Consistently charging to 100% or discharging to 0% increases stress.

High C-Rates (Fast Charging/Discharging): Increases temperature and side reactions.

Depth of Discharge (DoD): Larger discharge ranges typically shorten cycle life.

b) Environmental Conditions:

Temperature Extremes: Low temperatures hinder ion mobility; high temperatures accelerate chemical breakdown.

Storage Conditions: Long-term storage at high SOC and elevated temperatures worsens calendar aging.

c) Time:

Even unused batteries degrade over time due to internal chemical reactions—this is known as calendar degradation.

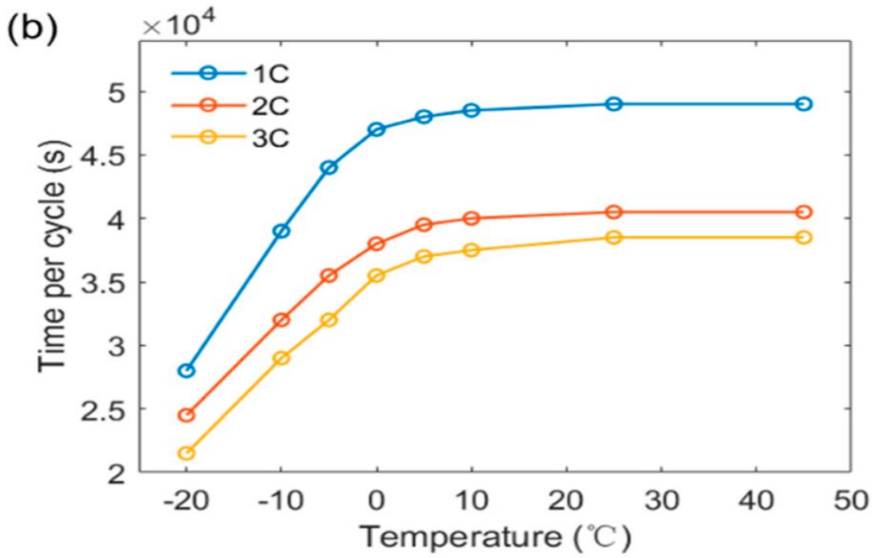

Figure (1.13): Time of single cycle under various operating modes.

1.7.4 Implications of Degradation

The consequences of battery degradation extend beyond technical performance:

- **Performance Impact:** In EVs, this translates to reduced driving range and slower acceleration. In BESS, degraded batteries offer reduced storage and power delivery capacity.
- **Economic Cost:** Degradation necessitates premature battery replacement, increasing lifetime ownership cost.
- **Environmental Impact:** Increased battery disposal and resource demand due to frequent replacements.

1.7.5 Managing and Mitigating Battery Degradation

While degradation is inevitable, its rate can be managed through thoughtful design and usage strategies:

a) Smart Charging Practices:

- Maintain battery charge between 20–80% for daily use.
- Limit the use of fast charging unless necessary.

b) Thermal Management:

- Use thermal management systems to maintain ideal temperature ranges (typically 15°C–35°C).
- Precondition EV batteries before use in extreme climates.

c) Battery Monitoring:

- Employ advanced Battery Management Systems (BMS) to track SOC, temperature, and charge/discharge rates.
- Regular diagnostics can detect early signs of degradation.

d) Usage Optimization:

- Avoid aggressive driving or high-load discharges when unnecessary.
- Schedule battery usage to minimize idle time at high charge levels.

1.8 Overview of Lithium-Ion Battery Architecture

1.8.1. General Description

Lithium-ion batteries are widely used energy storage devices, valued for their high energy density, lightweight construction, and stable voltage characteristics. They serve critical roles in applications such as portable electronics, electric vehicles, and energy storage systems. Their ability to deliver reliable power while minimizing size and weight is a key enabler for modern portable technologies.

1.8.2. Internal Structure

A typical lithium-ion battery features a three-layer, coiled internal structure encased in a cylindrical form. The major components include:

- **Positive Electrode (Cathode):** Typically composed of lithium cobalt oxide ($LiCoO_2$), serving as the lithium source during discharge.
- **Negative Electrode (Anode):** Constructed from highly crystalline specialty carbon materials.
- **Separator:** A porous membrane that physically isolates the two electrodes while allowing ionic transport.

The assembly also integrates critical safety components such as:

- **Pressure Release Valve:** To vent gases in the event of overpressure.
- **PTC Element:** To limit current flow during abnormal conditions.
- **Gaskets and Insulation Plates:** To enhance mechanical integrity and electrical isolation.

1.8.3 Electrochemical Reactions

The fundamental operation of lithium-ion batteries relies on the reversible transfer of lithium ions between electrodes during charge and discharge cycles. The simplified reactions are:

- **At the Positive Electrode (Cathode):**

$$LiCoO_2 \rightleftharpoons Li_{1-x}CoO_2 + xLi^{++xe^{-(1.2)}} \tag{1.2}$$

- **At the Negative Electrode (Anode):**

$$C + xLi^{++xe^{-\rightleftharpoons Li_xC}} \tag{1.3}$$

- **Overall Reaction:**

$$LiCoO_2 + C \rightleftharpoons Li_{1-x}CoO_2 + Li_xC \tag{1.4}$$

During charging, lithium ions migrate from the cathode to the anode, embedding into the carbon structure. Discharge reverses this process, delivering electrical energy to the external circuit.

1.8.4 Safety Features

To ensure operational safety, lithium-ion batteries are designed with:

- **Pressure Relief Systems:** Preventing internal rupture by releasing excess gases.
- **Current Interrupt Devices (CID) and PTC:** Limiting dangerous overcurrent events.

- **Thermal Management:** Reducing risk of overheating and thermal runaway.

1.9 Problem Statement

Lithium-ion battery degradation is a critical concern in energy storage and electric mobility, directly affecting system performance, safety, and lifecycle costs. As these batteries are increasingly deployed in electric vehicles (EVs), renewable energy systems, and portable electronics, there is a growing need for precise prediction of their aging behavior. However, battery degradation is influenced by multiple interacting factors—chemical, thermal, electrical, and mechanical—making it a highly complex process to model and monitor effectively.

A key challenge lies in the **inaccuracy of traditional battery capacity estimation methods**, which often rely on simplistic models or partial discharge cycles that fail to capture the nuanced aging mechanisms occurring within the cell. These conventional approaches typically lack the ability to provide real-time, reliable insights into a battery's internal condition, particularly under dynamic operational conditions. As a result, important indicators like State of Health (SoH), State of Charge (SoC), and Remaining Useful Life (RUL) are frequently misestimated, limiting the effectiveness of battery management systems and raising concerns for safety and performance.

Moreover, lithium-ion batteries exhibit varying degradation rates depending on their usage profiles, chemistry, and environmental conditions. While their standard lifespan ranges between 2–3 years in high-use scenarios, applications such as EVs demand operational durability of up to 15 years, complicating both experimental studies and practical deployment. Inaccurate degradation assessment not only hinders timely maintenance and replacement but also affects decisions in battery reuse and recycling, where reliable health estimation is essential.

Addressing these challenges requires a paradigm shift toward data-driven approaches. Techniques like Electrochemical Impedance Spectroscopy (EIS), when combined with deep learning models, offer a promising pathway to more accurate and scalable prediction of battery degradation.

1.10 Research Objectives and Scope

The objective of my thesis is to develop a deep learning-based approach for predicting battery degradation by estimating battery capacity over time. By leveraging data from the battery's lifecycle and impedance measurements, this work aims to extract meaningful health indicators and enhance the understanding of aging mechanisms in lithium-ion batteries.

This Memory specifically focuses on the identification and modeling of capacity degradation trends, with the goal of improving the accuracy of battery life prediction. The integration of deep learning techniques is intended to address the limitations of traditional estimation methods, which often struggle to capture the nonlinear and complex behavior of battery aging.

❖ **Research Objectives:**

- To investigate the applicability of deep learning models in predicting capacity degradation in lithium-ion batteries.

- To characterize degradation behavior using battery lifecycle and electrochemical impedance spectroscopy (EIS) data.
- To identify relevant health indicators that reflect the internal state and aging profile of the battery.

❖ **Research questions**

• How could the different battery degradations be characterized, when using battery life cycle data and electrochemical impedance spectroscopy data?

• What health indicators for battery degradations could be used?

• How could the battery degradations be predicted by using AI models and what accuracy could be achieved?

1.11 Conclusion

This chapter established a comprehensive foundation for understanding modern battery systems, particularly in the context of their degradation and the imperative for predictive analytics. It began by situating the role of electrochemical energy storage in key technological domains such as electric vehicles, portable electronics, and renewable energy integration. Through a systematic exploration of electrochemical principles, the internal architecture of batteries, and the dynamic interactions among their components, the chapter clarified how chemical processes govern charge-discharge behavior and performance metrics. Special attention was given to lithium-ion batteries due to their dominance in current and emerging applications, owing to their high energy density, relatively long cycle life, and favorable power-to-weight ratio. The discussion extended to thermal characteristics, degradation pathways, and the influence of operational stress factors such as temperature, depth of discharge, and charge rate. These aspects are central to the understanding of battery lifespan and reliability.

Furthermore, this chapter delineated the key performance indicators that are often used to evaluate battery systems, including energy density, power density, coulombic efficiency, and cycle life. These metrics provided a critical lens for assessing battery health and laid the groundwork for defining the targets of predictive modeling. By identifying both the physical limitations and the practical performance constraints of existing degradation over battery technologies, this chapter justified the need for advanced computational techniques capable of capturing the complex, nonlinear nature of battery time. This insight serves as a precursor to the integration of deep learning methodologies in battery capacity forecasting, which is explored in the subsequent chapters.

Chapter 2

Deep Learning Technology

2.1 Introduction

In recent years, there has been a significant increase in the adoption of machine learning across a wide spectrum of domains, ranging from research applications to industry use cases. This growing utilization encompasses tasks such as text mining, spam detection, video recommendation, image classification, and multimedia information retrieval.[23]

Within this context, deep learning has emerged as one of the most prominent approaches in machine learning. As a specialized subset of machine learning and artificial intelligence, deep learning is designed to mimic the human brain's capacity to process information and solve complex problems. It significantly extends the capabilities of traditional neural networks by leveraging advanced transformations and multi-layered architectures to extract hierarchical patterns from data.[24]

The field of deep learning has evolved rapidly, enabling the development of sophisticated models that outperform earlier machine learning techniques. These models rely on layered representations and are capable of learning from vast and complex datasets. Over time, deep learning has demonstrated its versatility and robustness across a wide range of application areas, including robotics, business analytics, cybersecurity, virtual assistants, healthcare, image recognition, natural language processing, and sentiment analysis.

This foundational shift has marked a transformative era in intelligent systems, positioning deep learning as a core technology in the advancement of artificial intelligence.

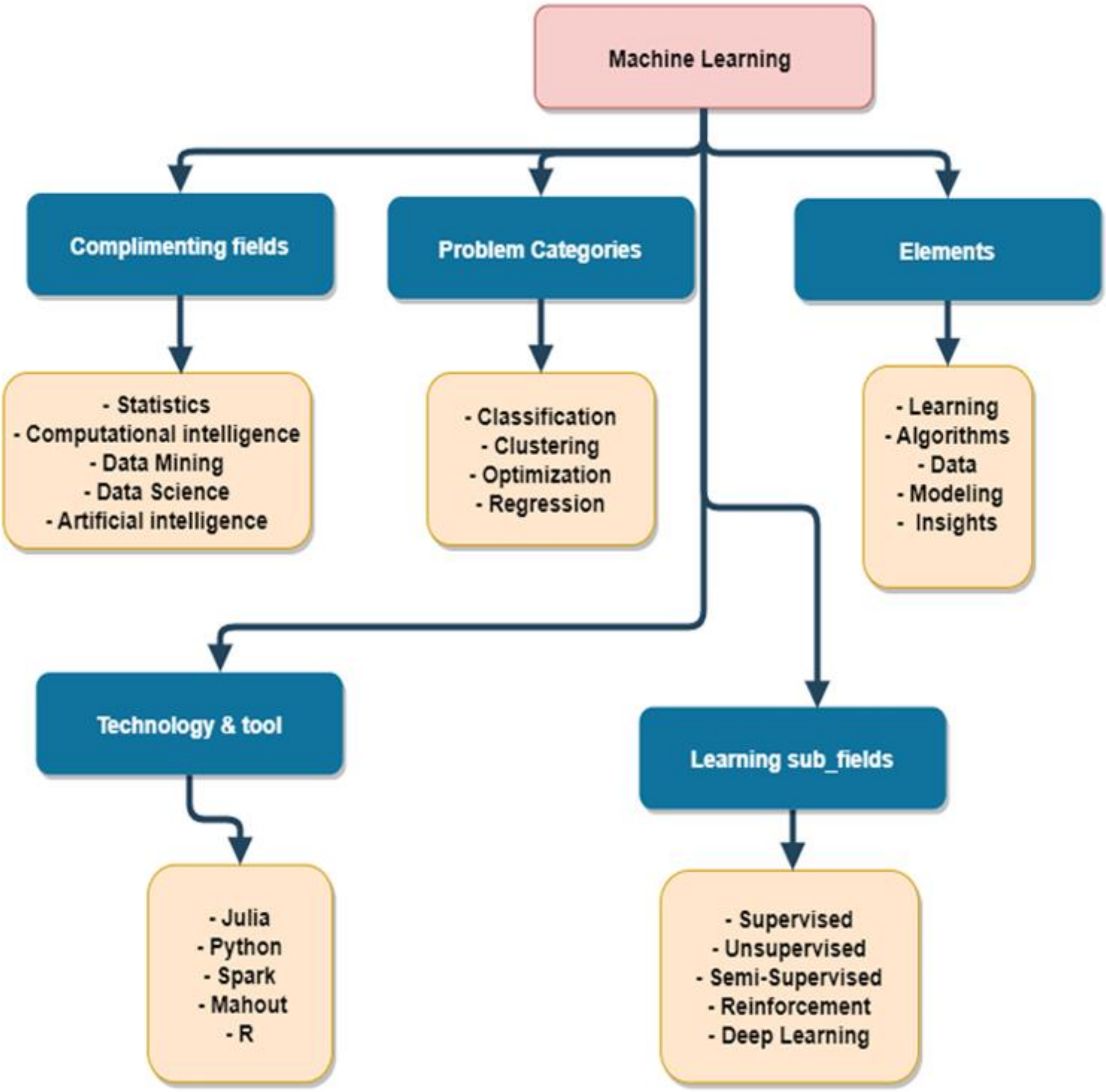

Figure (2.1): Machine Learning Parts

Among deep learning models, **Convolutional Neural Networks (CNNs)** have emerged as a powerful tool not only in image processing but also in time-series analysis, signal interpretation, and predictive maintenance tasks. CNNs are capable of extracting spatial and temporal features from multivariate data and have been successfully applied in various fields including autonomous systems, biomedical diagnostics, and now, increasingly, in energy systems.

This chapter provides a comprehensive literature review and theoretical foundation for CNNs, with a specific emphasis on their relevance to battery capacity prediction. We explore the evolution of CNNs, their fundamental working mechanisms, key architectural innovations, and their cross-domain applications — all of which serve to build the theoretical rationale for employing CNNs in our thesis work. The review further examines the limitations of current methods and highlights how CNN-based models address those challenges, especially in the context of large-scale battery lifecycle data and complex degradation behaviors.

This theoretical grounding forms the basis for the methodology adopted in this thesis, where CNNs are utilized to learn degradation patterns and estimate remaining useful life from the capacity trajectories of lithium-ion batteries under variable operating conditions.

2.2 Fundamentals of Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a class of deep, feedforward artificial neural networks originally designed to process data with grid-like topology, such as images. However, their architectural principles and learning capabilities have been successfully extended to one-dimensional (1D) and two-dimensional (2D) signal data, making them particularly relevant for time-series analysis and capacity prediction in lithium-ion batteries.[25]

At the core of CNNs lies the concept of **local connectivity**, **weight sharing**, and **hierarchical feature learning**. Instead of treating input data as flat vectors (as in traditional fully connected networks), CNNs preserve the spatial or temporal structure of the data. This is particularly beneficial when learning localized degradation features in battery capacity curves or identifying temporal dependencies in charging/discharging cycles.[26]

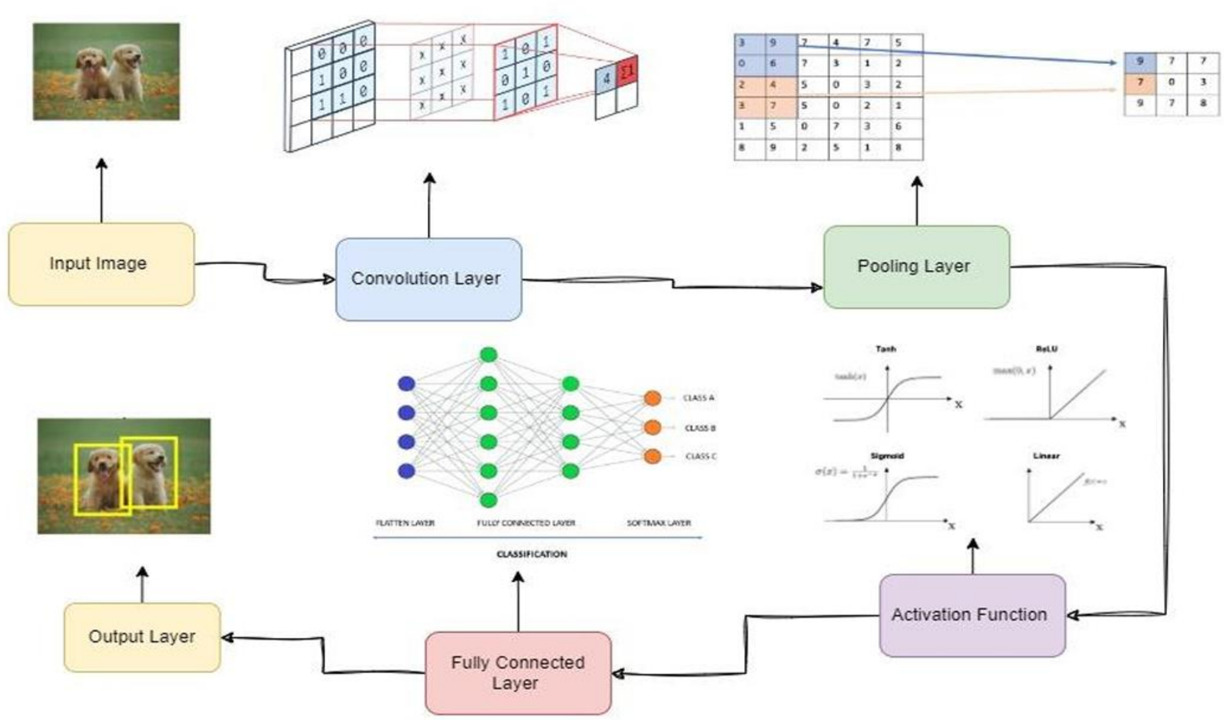

Figure (2.2): The CNN Components.

2.2.1 Convolution Operation

2.1.1 Input Image

Digital images are composed of pixels—individual units that encode the visual information of an image. These pixels are organized in a matrix form and have values ranging from 0 to 255, which define the brightness and color intensity of each point in the image.

When humans observe an image, the brain quickly processes vast amounts of visual information. Similarly, in convolutional neural networks (CNNs), the initial layers are designed to detect simple patterns such as edges, lines, and curves. Deeper layers then combine these low-level features to recognize more complex structures like faces or objects. This hierarchical learning mechanism enables CNNs to interpret images in a way that mimics human visual perception.[27]

2.1.2 Convolutional Layer

The convolutional layer is a foundational component of a CNN. It applies filters, also known as kernels, to the input data. Each filter has a defined height, width, and a set of weights. These weights are initialized randomly at the beginning of training and are progressively adjusted based on the learning process.

The convolution operation involves sliding a kernel across the input image and computing a dot product between the kernel and the corresponding sub-region of the image. This process generates a new representation known as a feature map, which highlights specific patterns detected by the kernel. The use of kernels allows CNNs to capture spatial hierarchies and localized features efficiently.

Each kernel operates in a high-dimensional space without explicitly computing the coordinates in that space. Instead, it relies on inner products between transformed data representations. This technique, often referred to as the "kernel trick," enables the transformation of linear models into non-linear ones, increasing the model's expressiveness.[28]

Unlike traditional neural networks that accept inputs as flat vectors, CNNs work directly with multidimensional image data. For example, grayscale images are single-channeled, while RGB images contain three separate channels for red, green, and blue.

To illustrate the convolution process, consider a 4×4 grayscale image and a 2×2 kernel with randomly initialized weights. As the kernel slides across the image both horizontally and vertically, it computes dot products at each position. These results populate the output feature map. For instance, a 4×4 input convolved with a 2×2 kernel produces a 3×3 output feature map, following the formula:

$$(K - L + 1) \times (K - L + 1) = (4 - 2 + 1) \times (4 - 2 + 1) = 3 \times 3$$

Each value in the resulting feature map represents a localized detection of a pattern, enhancing the ***network's ability to identify meaningful visual elements.***

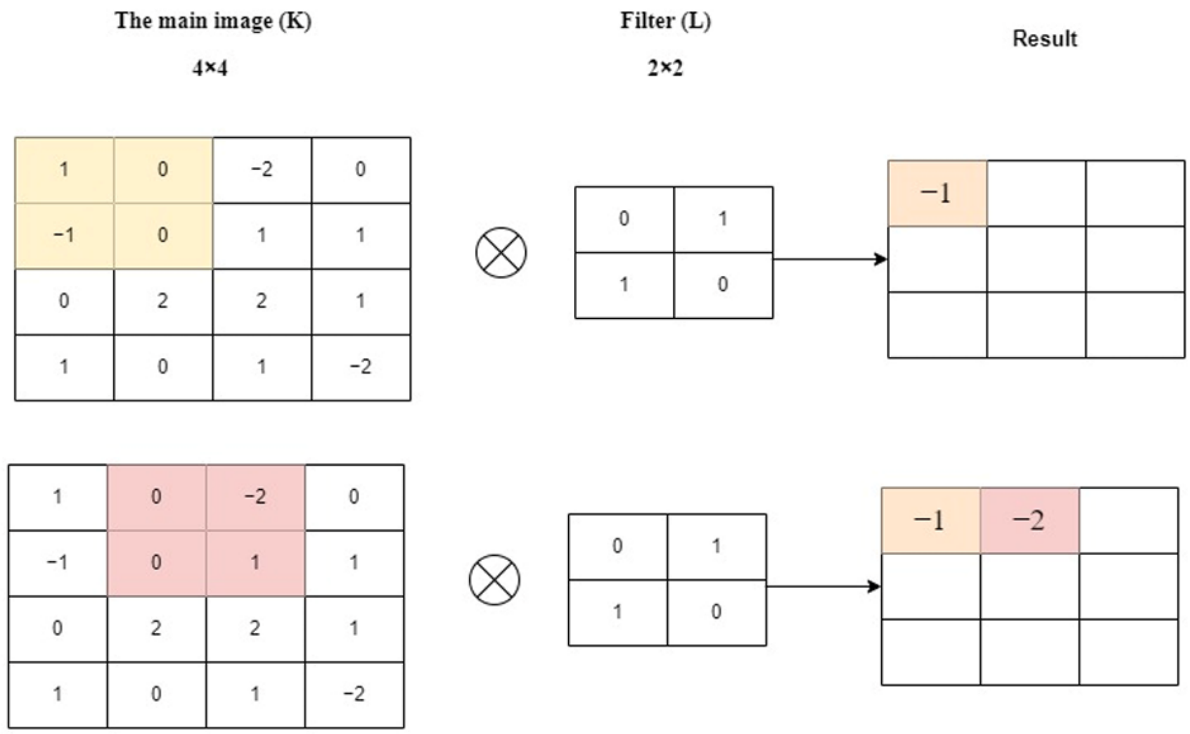

Figure (2.3): A visual representation of the primary calculations.

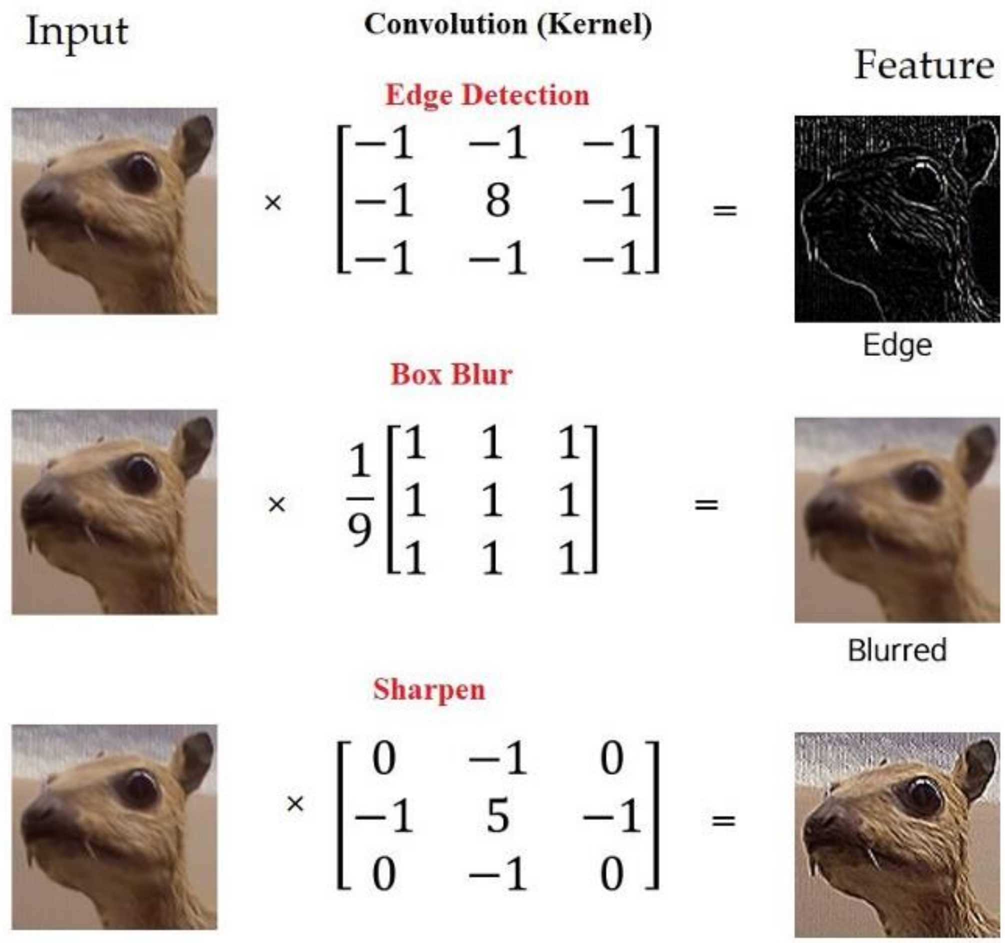

Figure (2.4): Effects of different convolution matrices

In CNNs, filters are initialized before training to become task-specific through the learning process.[29]

Weight Sharing: In CNNs, the complete set of weights acts uniformly on every pixel of the input matrix. There are no dedicated weights between individual neuron pairs across adjacent layers. Learning a single set of weights for the entire input significantly reduces training time and computational cost, as it eliminates the need to learn separate weights for each neuron.

Stride: CNNs also offer additional options to further refine configuration and mitigate undesirable effects. One such parameter is the stride. In the earlier scenario, the next-layer node overlaps substantially with neighboring nodes due to the sliding window's default movement. By adjusting the stride, the degree of overlap can be modified. For example, consider a unique 6×6 image as shown in Figure 5. With a stride of 1, the filter can only move one node at a time, resulting in a maximum output size of 4×4. As depicted, there is evident overlap among the outputs of the left, center, and right sections. However, if the stride is increased to 2, the filter steps over every two nodes, and the output is reduced to 3×3. In essence, increasing the stride reduces both the output size and the degree of overlap.[29]

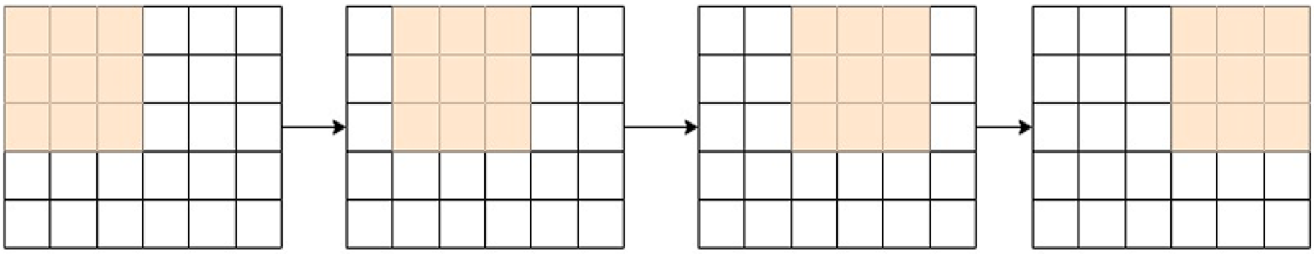

Figure (2.5): Stride1, the filter windows move only one time for each connection

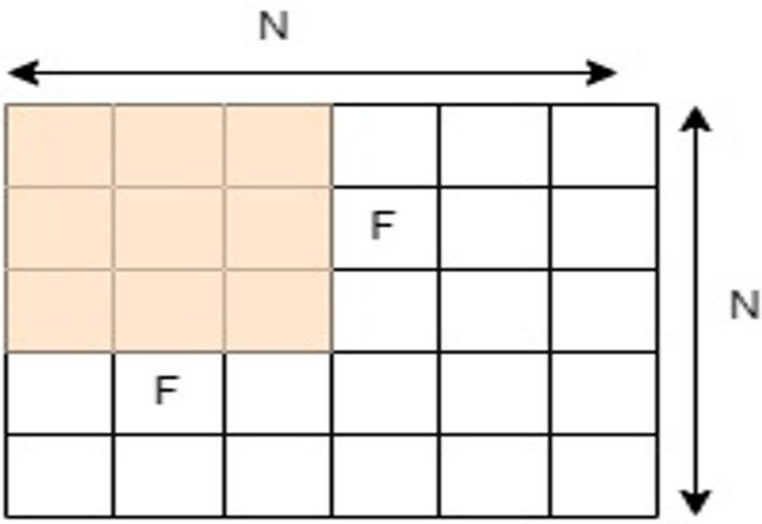

Figure (2.6): The effect of stride in the output.

Equation (2) formalizes this, resulting in the output size O as shown in Figure 6, given the image's NXN dimension and FXF filter size.

$$O = 1 + \frac{(N - F)}{S} \quad (2.1)$$

where N is the input size, F is the filter size, and S is the stride size.

Padding

One disadvantage of the convolution step is the potential loss of detail at the image's edges, as these regions are only captured when the filter moves over them and are otherwise not considered. A simple and effective solution to this issue is the use of zero padding. Zero padding also helps in managing the output size.

For example, in Figure 6, the output size would be 4 × 4 when starting from a 6 × 6 input, using a filter size F=3, input size N=6, and a stride of 1.

However, by applying a one-layer zero padding, the output becomes 6 × 6, thus matching the original input size. The effective input size with padding becomes 9. The output size with zero padding can be calculated using the modified formula:

$$O = 1 + \frac{(N + 2P - F)}{S} \quad (2.2)$$

where P is the number of zero-padding layers (e.g., P=1 in Figure 7). By using this padding concept, the decrease in network output size with depth can be prevented, making it feasible to construct deep convolutional networks without progressively shrinking the spatial dimensions.

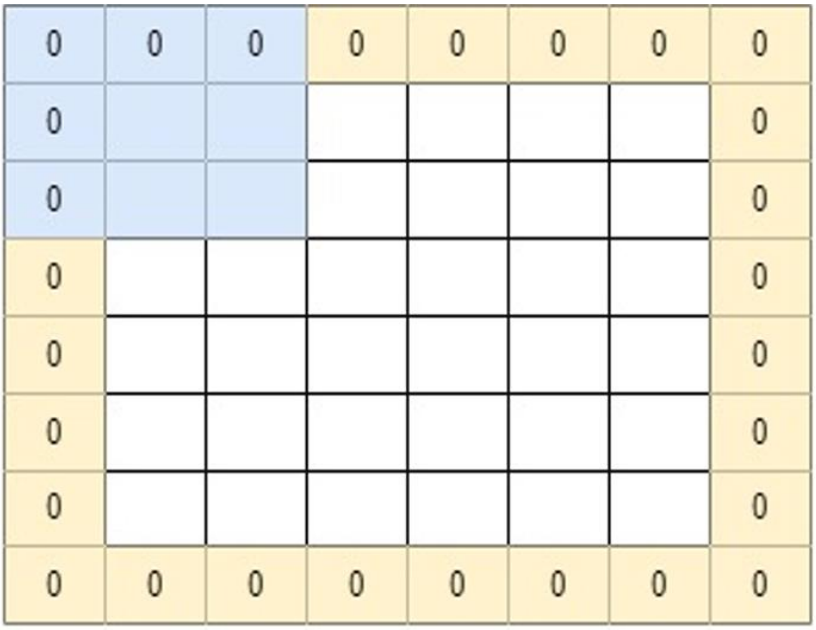

Figure (2.7): Zero-padding.

2.1.3 Pooling

The pooling layer, also referred to as the down-sampling layer, is used to reduce the dimensionality of the feature maps while preserving the most critical information. This is achieved through the application of a filter that slides over the input data, performing pooling operations such as maximum, minimum, or average pooling. Among these, maximum pooling is the most commonly used in practice.

The core function of pooling is down-sampling, which reduces the complexity of the subsequent layers. In the context of image processing, this is analogous to lowering the resolution. Notably, the number of filters remains unchanged during pooling. Max pooling is widely applied, where the input image is divided into rectangular subregions, and the maximum value within each subregion is retained. A common pooling size is 2 × 2.

As illustrated in Figure 8, when pooling is applied to 2 × 2 blocks, for example in the top-left corner of an image, the operation shifts focus to the top-right corner in steps. This movement typically uses a stride of 2. Although less common, a stride of 1 can be used to avoid down sampling. It is important to note, however, that down sampling inherently does not preserve the exact spatial location of the data.

$f_{max}(x) = max(x_1, x_2, \ldots, x_n)$(2.3)

In our application, pooling layers help distill battery signal characteristics by summarizing feature regions, aiding in robust degradation pattern recognition.

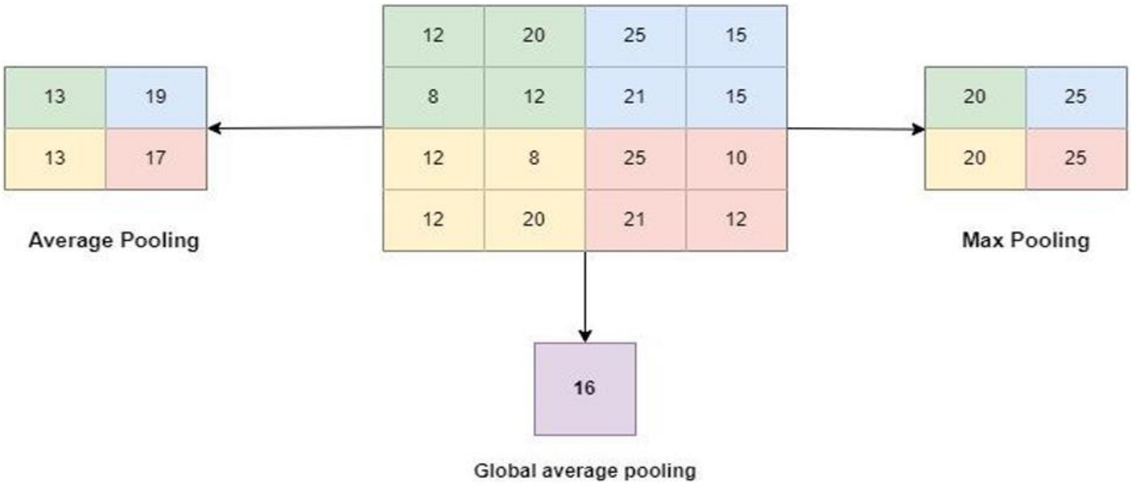

Figure (2.8): Pooling Layer.

2.1.4. Non-Linearity (Function of Activation)
The non-linearity layer follows the convolution layer. This layer allows the generated output to be modified or suppressed. It is used to restrict or oversaturate the output as needed. Every type of activation function in a neural network serves the essential role of mapping input to output.

The input to an activation function is calculated by determining the weighted sum of a neuron's inputs and its bias (if present). The activation function then decides whether or not the neuron should be activated based on this value by producing the corresponding output.

In the CNN architecture, non-linear activation layers follow all layers with weights (also known as learnable layers), such as fully connected (FC) layers and convolutional layers. These activation layers introduce non-linearity, enabling the CNN to learn highly complex representations.[30]

Another critical property of activation functions is differentiability, which is necessary to apply error backpropagation during network training.[31].

The most commonly used activation functions in CNNs and deep neural networks include:

- **Sigmoid**: Accepts real numbers as input and maps the output to a range between 0 and 1.
- **Tanh**: Similar to the sigmoid function but maps input values to a range between -1 and 1.

- **ReLU (Rectified Linear Unit)**: The most widely used activation function in CNNs. It converts all input values to the positive domain.[32]

  ReLU's main advantage over other functions lies in its computational efficiency, which reduces time and resource consumption.

For many years, sigmoid and tanh functions were the most common non-linearities. However, due to their advantages, rectified linear units have gained significant popularity in recent years. Various types of non-linear activation functions are illustrated in Figure 9.

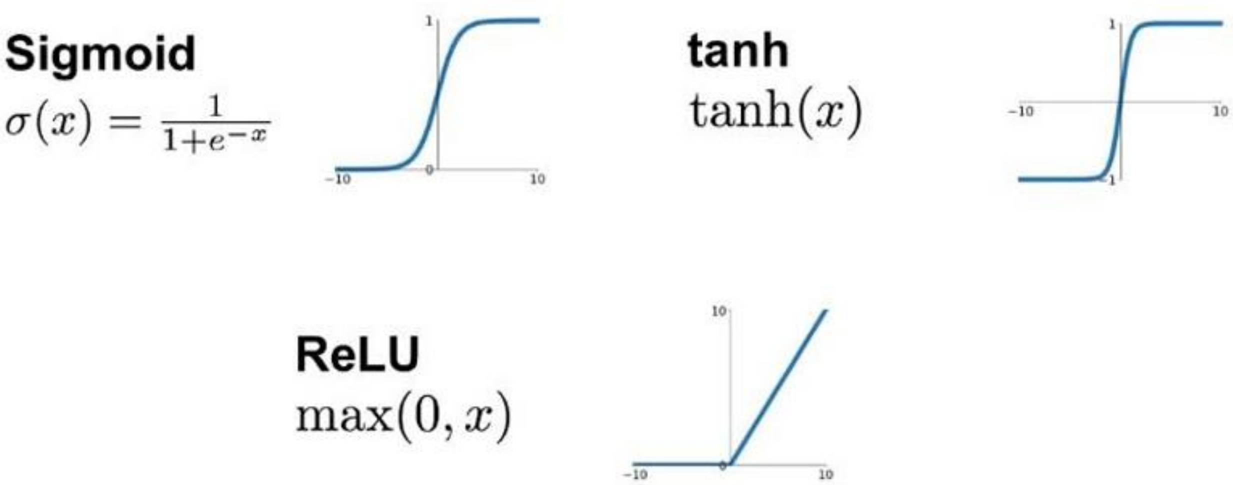

Figure (2.9): Function of Activation

2.1.5. Fully Connected Layer

Neurons in the fully connected (FC) layer are arranged similarly to traditional feedforward neural networks. In this configuration, every neuron in one layer is connected to every neuron in the next layer. As illustrated in Figure 10, each node in the latest pooling layer is flattened into a one-dimensional vector and fully linked to the neurons in the FC layer above it. [33]

The primary function of this layer is to perform high-level reasoning and classification based on the features extracted by preceding convolutional and pooling layers. The output of a fully connected layer can be computed using the following formula: [34]

$y = f(Wx + b)$(2.4)

Where:

- $y$is the output vector,
- $W$is the weight matrix,
- $x$is the input vector (flattened feature map),
- $b$is the bias vector,
- $f$is the activation function (e.g., ReLU or Sigmoid).

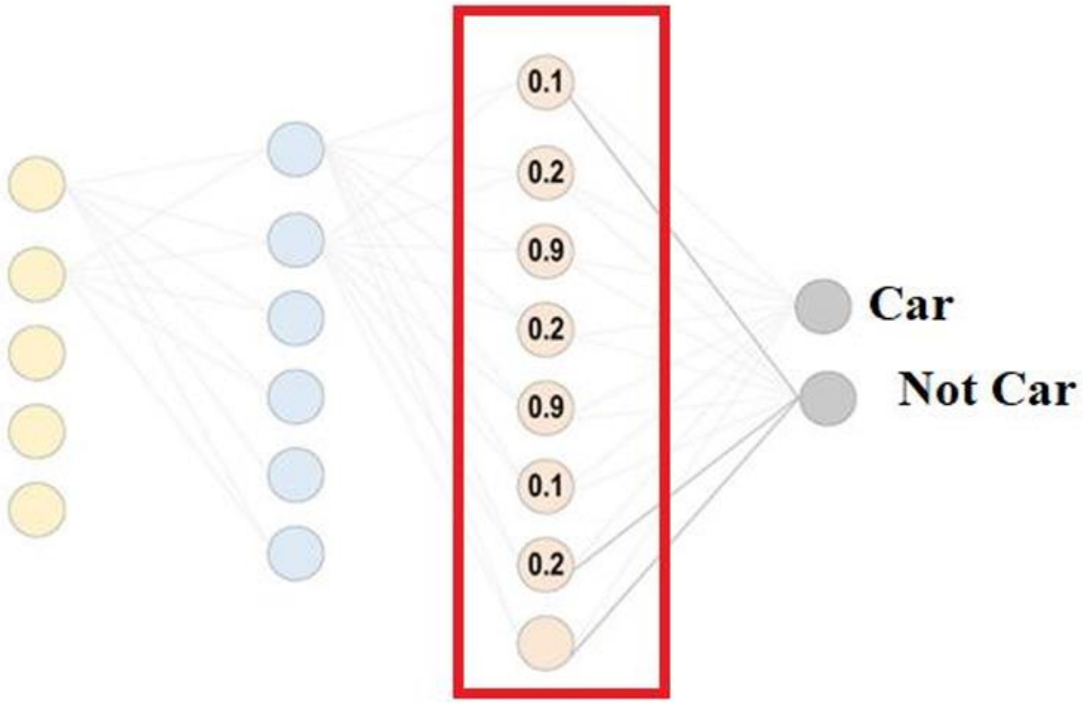

Figure (2.10): Fully-connected layer

The loss function, however, takes advantage of two inputs to pinpoint the source of the mistake. For CNN, the first parameter is the forecast or estimated output. The second input is the desired output or label.

There are many different kinds of loss functions used for different sorts of problems. Output value of the previous layer.

Training: A training dataset made up of a collection of images and labels (classes, bounding boxes, and masks) is used to train a CNN model. Backpropagation is a CNN training procedure that measures an error value using the error value

Each neuron's weight in that layer is updated using the in order to measure an incorrect value and revise the old weights, fresh weights are Below is a basic explanation of the many kinds of loss functions: employed, as shown in Figure 11.

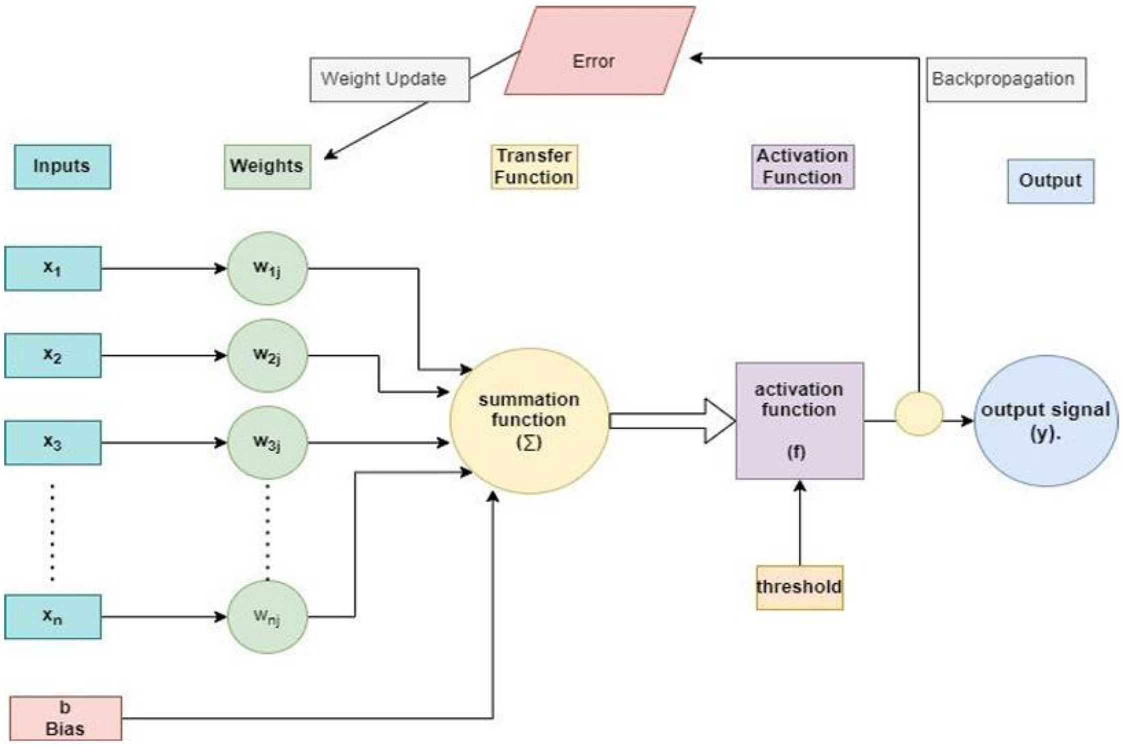

Figure (2.11): forward and backpropagation in hidden CNN layers.

Until it reaches the first layer, the algorithm repeats the procedure. All inputs, including the bias unit, are summarized by the activation unit, then, use the activation function to compute the result. The network will then calculate the cost function and send the error back to update the weights until the cost is minimized.

2.3 Regularization of CNN

When trying to create well-behaved generalizations for CNN models, over-fitting is the key obstacle. Over-fitting describes a situation in which a model does well on training data but poorly on test data (data it has never seen before), as will be shown in the next section. [35]

When the model does not pick up enough information from the training data, it is said to be under-fitted. A model is considered to be "just fit" if it produces

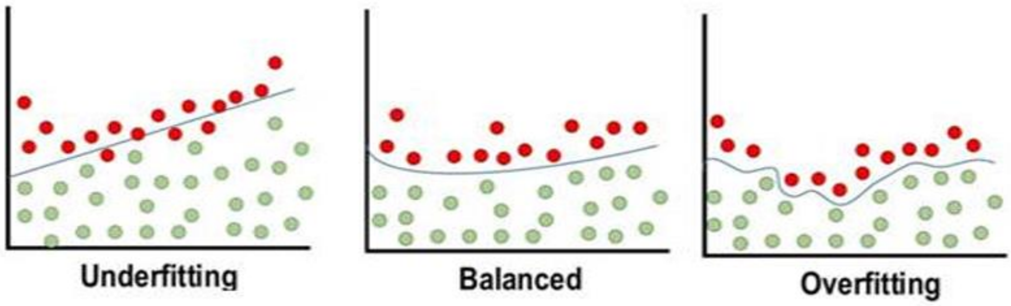

Figure (2.12): Regularization to CNN

satisfactory results on both the training and testing data. These three types are shown in Figure 12.

Multiple intuitive techniques are employed to facilitate regularization and prevent overfitting. Overfitting and underfitting are critical concerns in training neural networks, and various strategies are used to mitigate these risks.

Dropout is one of the most widely used generalization strategies. During each training iteration, a random subset of neurons is temporarily removed (or "dropped") from the network. This forces the model to learn redundant representations and ensures that no single neuron becomes overly specialized. As a result, feature selection becomes more balanced across the network. A dropped neuron does not participate in either forward or backward propagation during training. However, during testing, the full network is used for prediction, with weights typically scaled to account for the dropout during training.[36]

A similar approach, **drop-weight**, eliminates the weights (connections) between neurons after each training iteration rather than removing the neurons themselves [37] .

Another effective method to combat overfitting is **data augmentation**, which artificially expands the training dataset by applying transformations such as rotation, scaling, flipping, and cropping to existing images. This process helps improve the model's ability to generalize by exposing it to a broader variety of input data.[38]

Batch normalization is another powerful technique that stabilizes and accelerates training. It standardizes the inputs to each layer by subtracting the batch mean and dividing by the batch standard deviation. This normalization follows the formulation of a unit Gaussian distribution:[39]

$$\hat{x} = \frac{x-\mu}{\sqrt{\sigma^2+\epsilon}} \tag{2.5}$$

Where:

- $x$is the input activation,
- $\mu$is the batch mean,
- $\sigma^2$is the batch variance,
- ϵepsilonϵ is a small constant to prevent division by zero.

Though it resembles a preprocessing operation, batch normalization is fully differentiable and integrated within the training process. It effectively reduces **internal covariate shift**, a phenomenon where the distribution of inputs to a layer changes during training due to weight updates. This is especially helpful when dealing with data from diverse sources (e.g., day vs. night images).

To counter this variability and improve model stability, batch normalization layers are inserted within the CNN architecture. The key benefits include:

- Preventing vanishing gradients early in training,
- Improving robustness to poor weight initialization,
- Reducing training time by accelerating convergence,
- Decreasing sensitivity to hyperparameters,
- Providing mild regularization, thereby reducing overfitting likelihood.

2.4 Backpropagation and Learning

CNNs are trained using supervised learning with **backpropagation** and **gradient descent**. During training, the model updates the weights of filters and connections to minimize a loss function, often the **mean squared error (MSE)** when predicting continuous values like capacity.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (2.6)$$

where $y_i$is the true battery capacity at cycle i and $\hat{y}_i$ is the predicted value.[40]

2.5 CNN Architectures and Evolution

The architecture of Convolutional Neural Networks (CNNs) has evolved significantly since their inception, driven by the need to address increasing data complexity, depth requirements, and computational challenges. The architecture adopted for a particular task — such as battery capacity prediction — must balance model expressiveness, training feasibility, and generalization capability. This section outlines key architectural advances in CNNs and contextualizes their relevance to predictive tasks involving time-series and degradation data.

2.5.1 LeNet-5: The Foundational Model

One of the earliest CNN architectures, **LeNet-5**, introduced by LeCun et al. (1998), demonstrated the feasibility of using convolution and subsampling layers for image classification tasks. It consisted of two convolutional layers, two pooling layers, and two fully connected layers.[41]

Although originally designed for character recognition, LeNet-5's layered feature extraction paradigm has inspired many domain-specific adaptations. In battery health prediction, similar shallow CNN configurations can be employed when datasets are limited or when model interpretability is prioritized over depth.

2.5.2 AlexNet and Deeper Architectures

The introduction of **AlexNet** (Krizhevsky et al., 2012) marked a paradigm shift in CNN design. AlexNet leveraged deeper architectures with multiple convolutional layers, ReLU activations, dropout regularization, and GPU acceleration, enabling breakthroughs in image classification.

For applications in battery diagnostics, deeper networks such as AlexNet variants can capture more complex degradation patterns, especially when large-scale datasets are available, such as full cycle life data from multiple battery cells. [42]

2.5.3 VGGNet: Depth with Simplicity

VGGNet (Simonyan and Zisserman, 2014) demonstrated that the depth of a CNN could be increased effectively using small 3×33 \times 33×3 filters. This modular design provided both high performance and architectural clarity.

In the context of lithium-ion battery analysis, VGG-like architectures can be adapted to model long-term temporal dependencies across charge-discharge cycles, where each cycle is treated as a spatial-temporal frame in a 2D matrix. [43]

2.5.4 ResNet: Residual Learning

ResNet (He et al., 2015) introduced **residual connections** to mitigate the vanishing gradient problem in very deep networks. These shortcut connections allow the model to learn identity mappings, enabling efficient training of networks exceeding 100 layers.

Battery capacity degradation over hundreds of cycles can involve subtle, long-range temporal patterns. Residual blocks allow CNNs to model such dependencies without loss of signal propagation or gradient flow during training, which is vital in predictive maintenance and health estimation models. [44]

2.5.5 Lightweight Architectures: MobileNet and EfficientNet

Recent trends favor **lightweight CNNs** like **MobileNet** and **EfficientNet**, designed for deployment in resource-constrained environments. These models utilize techniques such as **depthwise separable convolutions**, **bottleneck blocks**, and **compound scaling**.

Given the increasing integration of battery diagnostics into edge devices and embedded systems (e.g., Battery Management Systems), such lightweight CNNs offer promising pathways for real-time, on-device prediction of battery state-of-health (SOH) and remaining useful life (RUL).

The evolution of CNN architectures illustrates the trade-offs between depth, complexity, computational demand, and prediction accuracy. For our thesis on battery capacity prediction using deep learning, these architectural insights guide the selection and customization of 2D CNNs that balance predictive performance with model interpretability and scalability.

2.6 Applications of CNNs in Battery Diagnostics

Convolutional Neural Networks (CNNs) have emerged as a powerful tool for processing structured and unstructured data in battery systems, especially in tasks that involve pattern recognition, temporal signal correlation, and feature abstraction. In the domain of lithium-ion battery diagnostics, CNNs offer substantial promise for enhancing both the accuracy and interpretability of degradation assessments and capacity prediction.

2.6.1 State-of-Health Estimation

One of the most critical applications of CNNs in battery diagnostics is the estimation of **State-of-Health (SoH)**. The SoH indicates the current performance condition of a battery relative to its nominal state. CNNs are able to learn complex mappings between raw input data (such as voltage profiles, current loads, and impedance spectra) and corresponding health states. For example, 1D CNNs have been effectively applied to time-series data derived from charging cycles to forecast SoH trajectories.

This capability is particularly relevant for predicting SoH across various aging scenarios, including fast charging regimes, irregular load patterns, and temperature-induced degradation — all of which are highly nonlinear and difficult to model with traditional physics-based techniques.

2.6.2 Remaining Useful Life (RUL) Prediction

Predicting the **Remaining Useful Life (RUL)** of a battery is vital for ensuring safety, reducing maintenance costs, and improving scheduling for battery replacement. CNNs, especially when combined with recurrent architectures or trained on degradation trajectories, can accurately extract features that capture the early signals of degradation.

When trained on complete cycle-life datasets, CNN-based models can generalize to unseen early-cycle data from new cells, enabling robust RUL forecasting. In real-world electric vehicle (EV) scenarios, this allows early identification of batteries approaching end-of-life.

2.6.3 Fault Detection and Classification

CNNs have also been employed for **fault detection and classification**, particularly in identifying anomalies in battery behavior that may signal internal shorts, thermal runaway, or overcharging. The spatial feature extraction capabilities of CNNs are well suited for analyzing spectrograms or 2D representations of EIS (electrochemical impedance spectroscopy) data.[45]

Studies have shown that CNNs trained on EIS maps or current-voltage heatmaps can outperform traditional classifiers in detecting incipient failure modes — supporting predictive maintenance strategies in grid-scale storage systems or fleet-based EV monitoring.

2.6.4 Data-Driven Feature Engineering

Another key strength of CNNs lies in their ability to **automatically learn hierarchical features** from raw input data, thereby reducing the need for manual feature engineering. This is particularly useful in battery diagnostics, where handcrafted features based on domain heuristics often fail to generalize across different chemistries, form factors, and operating conditions.

By learning directly from high-dimensional datasets, CNNs allow for scalable and flexible modeling pipelines that adapt to various battery datasets, including voltage-time curves, internal resistance trajectories, and impedance spectra.

2.6.5 Transfer Learning and Domain Adaptation

Recent developments in CNN-based battery diagnostics include the application of **transfer learning**, where pretrained CNN models on one dataset (e.g., a specific cell chemistry) are fine-tuned on a smaller dataset from a different context. This is particularly beneficial when labeled battery data is limited, a common challenge in the field.

CNNs also support **domain adaptation** techniques, enabling models to generalize across different operating conditions or cell manufacturers. These approaches enhance the robustness of battery life prediction tools and make them viable for real-world BMS deployment.

2.7 Deep Learning versus Traditional Machine Learning for Battery Capacity Prediction

The prediction of battery capacity and degradation trends is a critical task in modern energy storage research, particularly for lithium-ion batteries used in electric vehicles and portable electronics. While traditional machine learning (ML) methods have provided promising results, deep learning (DL) approaches—particularly those employing Convolutional Neural Networks (CNNs)—offer significant improvements in scalability, accuracy, and feature representation. This section compares the capabilities and limitations of these two paradigms in the context of battery diagnostics and capacity prediction.

2.7.1 Feature Engineering and Representation Learning

Traditional ML models, such as Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting Machines (GBM), typically require extensive manual feature engineering. Domain knowledge is often used to extract statistical or physics-informed features from raw data such as voltage curves, differential capacity plots, or impedance spectra. However, these handcrafted features may not generalize well across different battery chemistries, usage patterns, or manufacturers.

In contrast, deep learning methods—especially CNNs—automatically learn hierarchical feature representations from raw or minimally preprocessed data. This ability to perform end-to-end learning reduces dependency on domain expertise and increases model adaptability to diverse datasets. For example, CNNs can directly process entire charging/discharging curves or time-frequency representations without requiring transformation into engineered indicators.

2.7.2 Modeling Nonlinear Relationships

Battery degradation is governed by highly nonlinear and coupled electrochemical processes that are influenced by variables such as temperature, current rate, cycle history, and mechanical stress. Traditional ML models often struggle to capture these complex temporal and spatial dependencies without significant tuning.

Deep learning models, by virtue of their multi-layered architectures, can capture high-dimensional nonlinear mappings effectively. CNNs, in particular, can identify local and global patterns across input signals, enabling more accurate capacity predictions even under varying operational conditions or noise-corrupted measurements

2.7.3 Scalability and Generalization

In battery diagnostics, scalable modeling is essential for accommodating large and heterogeneous datasets, especially in real-world fleet applications. Traditional ML models may suffer from performance degradation when trained on high-dimensional data due to the curse of dimensionality and overfitting.

Deep learning models—especially when trained with large annotated datasets—can generalize more effectively, particularly through regularization techniques such as dropout, batch normalization, and data augmentation. CNNs are inherently suited for scalable learning, leveraging GPU acceleration and parallelization, which is critical for processing large volumes of cycle life or impedance data.

2.7.4 Interpretability and Transparency

One of the longstanding criticisms of deep learning models is their limited interpretability compared to traditional ML approaches. Techniques like decision trees or SHAP (SHapley Additive exPlanations) values in tree-based models offer clearer insights into feature contributions. In battery management systems (BMS), where decisions may have safety implications, this is a significant consideration.

However, recent advancements in explainable AI (XAI) have improved the interpretability of deep learning models. CNNs can now be analyzed using saliency maps, gradient-weighted class activation mapping (Grad-CAM), and layer-wise relevance propagation to highlight important features or input regions influencing the prediction outcome.

2.7.5 Performance in Real-World Applications

Empirical evidence suggests that deep learning models outperform traditional ML techniques in several battery-related tasks. Studies involving real-world datasets from fast-charging batteries or diverse cycling scenarios have shown that CNNs can achieve lower prediction errors and higher robustness against data noise and imbalance.

Furthermore, CNN-based architectures can be integrated into embedded systems or cloud platforms for online monitoring and real-time diagnostics, a challenge for more memory-intensive traditional ML models.

2.8 Limitations and Challenges of Deep Learning in Battery Prognostics

Despite the demonstrated advantages of deep learning in battery state prediction, the deployment of such models in real-world battery management systems (BMS) is subject to several limitations and challenges. These obstacles must be addressed to ensure the robustness, reliability, and safety of AI-driven prognostic tools for lithium-ion batteries.

2.8.1 Data Availability and Quality

Deep learning models are inherently data-hungry. Their performance relies heavily on the availability of large, diverse, and high-quality datasets encompassing various battery chemistries, cycling conditions, and aging mechanisms. In practice, collecting such comprehensive datasets is a significant bottleneck. Batteries degrade slowly, and acquiring full life-cycle data under controlled conditions requires months or even years of experimentation. Additionally, publicly available datasets often lack standardized formats, include missing or noisy data, and may not reflect the full range of usage scenarios encountered in real-world applications.

2.8.2 Lack of Generalizability Across Battery Types

Deep learning models trained on one type of battery chemistry or under a specific operational profile often struggle to generalize to other chemistries or conditions. For example, a model trained on nickel manganese cobalt oxide (NMC) batteries might perform poorly when applied to lithium iron phosphate (LFP) batteries. This lack of cross-domain adaptability is a critical challenge, especially for commercial applications where multiple battery types may coexist.

2.9 Future Outlook and Implications for Battery Prognostics

The preceding review has established a strong theoretical foundation for using Convolutional Neural Networks (CNNs) in battery health monitoring and capacity prediction. CNNs have shown superior performance in learning hierarchical representations and extracting critical patterns from complex, multi-dimensional lithium-ion battery datasets. Their ability to model nonlinear degradation and cell variability makes them well-suited for estimating State-of-Health (SoH), Remaining Useful Life (RUL), and other prognostic metrics.

CNNs have also proven effective when integrated with deep learning components like LSTMs, GRUs, and attention mechanisms, offering temporal sensitivity and improved accuracy. Furthermore, the use of optimization algorithms for hyperparameter tuning has significantly enhanced prediction quality. These developments contribute to the growing viability of intelligent Battery Management Systems (BMS), especially for electric vehicles and energy storage applications.

However, CNN-based methods pose computational challenges. The accuracy and performance of CNNs are highly dependent on architectural choices, including the number and configuration of convolutional and pooling layers, filter sizes, stride values, and placement of pooling operations. Training such networks requires substantial computing power, particularly GPUs, and demands extensive parameter tuning. Even minor changes in hyperparameters can significantly affect results, highlighting the need for careful optimization.

As CNN architectures evolve—transitioning from shallow models like AlexNet to deeper networks such as ResNet, DenseNet, and others—there is a trend toward developing compact models that maintain performance while reducing computational costs. Lightweight CNNs, enhanced by techniques such as knowledge distillation and improved pre-training strategies, offer a promising direction for real-time battery prognostics, particularly in resource-constrained embedded environments.

These insights form the rationale for the CNN-based methodology adopted in this thesis. The framework described in the next chapter incorporates full-cycle battery data and a carefully optimized CNN architecture to predict capacity degradation under real-world conditions.

2.10 Conclusion

In this chapter, the conceptual and technical landscape of deep learning was thoroughly examined with a particular focus on its applicability to battery capacity prediction. As traditional empirical and physics-based models struggle to generalize across varying battery chemistries and usage profiles, deep learning—especially convolutional neural networks (CNNs)—has emerged as a robust and scalable alternative. The discussion outlined the hierarchical nature of deep learning models, emphasizing the strength of CNNs in processing structured, high-dimensional data such as time series derived from battery cycling.

Core architectural elements of CNNs were dissected, including convolutional layers for local pattern recognition, activation functions for non-linearity, pooling layers for spatial abstraction, and fully connected layers for decision mapping. These elements enable the model to automatically learn degradation signatures embedded in voltage, temperature, and capacity profiles. Furthermore, the chapter provided a comparative review of state-of-the-art research, illustrating how CNNs outperform conventional regression and rule-based systems in terms of prediction accuracy and adaptability to diverse datasets.

The theoretical exposition was grounded in the context of battery health monitoring, demonstrating how CNNs can transform raw multivariate data into meaningful predictive features without requiring manual feature engineering. This capability is especially advantageous when dealing with the complex and stochastic behavior of battery degradation. Ultimately, this chapter served to bridge the gap between electrochemical theory and intelligent computation, laying a strong foundation for the system implementation discussed in Chapter 3. The integration of deep learning into battery diagnostics not only represents a methodological innovation but also holds significant promise for improving the safety, reliability, and efficiency of energy storage systems.

Chapter 3

Battery Cycle Life Prediction Using Deep Learning

3.1 Introduction

The accurate prediction of lithium-ion battery cycle life remains a challenging task due to the inherent complexity of the underlying degradation mechanisms. Traditional physics-based models often fail to capture the variability introduced by diverse operational conditions and inconsistencies in manufacturing processes. Even batteries produced by the same manufacturer under nominally identical conditions may exhibit substantial differences in aging behavior, making deterministic modeling approaches insufficient for reliable prognostics.[46]

In this work, a data-driven approach utilizing deep learning techniques is adopted to estimate the remaining cycle life of fast-charging lithium-ion batteries. Specifically, a two-dimensional Convolutional Neural Network (2D-CNN) architecture is employed to learn complex patterns from historical cycling data and to predict the number of remaining cycles before the battery reaches its end-of-life criterion. This threshold is defined as the point at which the battery's capacity drops to 80% of its initial nominal value.[47]

3.2 Data Description

The dataset used for model development comprises cycling measurements collected from 40 lithium-ion battery cells. Each cell features a nominal capacity of 1.1 Ah and a nominal voltage of 3.3 V. The batteries were subjected to a variety of predefined charge and discharge protocols designed to emulate different operational scenarios.

Each battery was cycled continuously until it reached 80% of its initial capacity. The total number of charge-discharge cycles required to reach this degradation point defines the cycle life of the respective cell. Notably, this cycle life varies substantially across the dataset, ranging from as few as 150 cycles to as many as 2300 cycles, reflecting the influence of operational and intrinsic factors on battery longevity.[48]

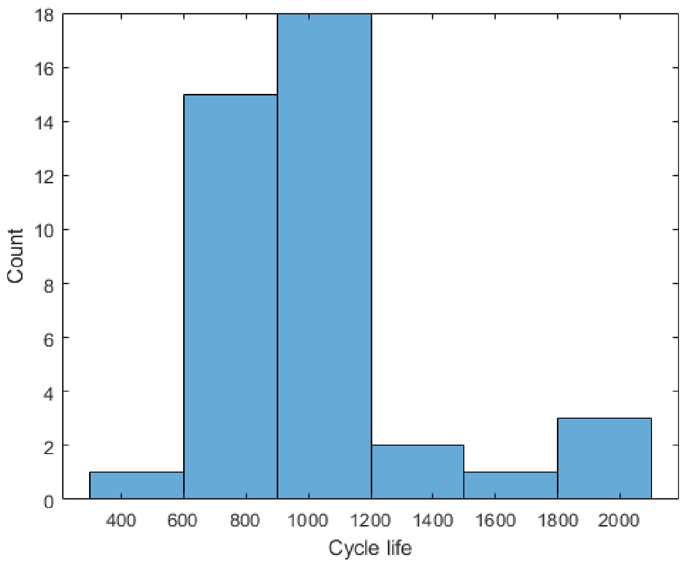

figure (3.1): measurements from 40 cells

3.3 Data Acquisition and Structure

While the full dataset comprises measurements from 124 individual lithium-ion cells, the present work utilizes a curated subset consisting of 40 cells. This reduction serves the dual purpose of ensuring computational efficiency and simplifying the implementation and testing of the proposed deep learning model. Nevertheless, this subset maintains sufficient diversity in cell behavior to allow for meaningful training and evaluation.

For each of the 40 battery cells, data are organized into structured arrays containing key electrochemical parameters recorded over successive charge-discharge cycles. Specifically, the following measurements are available within each cycle:

- **Current (A):** The electrical current applied during the charge and discharge phases.
- **Voltage (V):** Terminal voltage recorded across the cell during operation.
- **Temperature (°C):** The cell temperature measured during cycling, reflecting thermal dynamics.
- **Capacity (Ah):** The measured charge capacity of the battery during the discharge process.
- **Differential Discharge Capacity (dQ/dV):** The derivative of capacity with respect to voltage, a feature known to provide insights into degradation patterns and electrochemical shifts.

These features provide a rich, multi-dimensional representation of each cell's behavior over time and are instrumental for training a deep learning model capable of learning from complex temporal and nonlinear dependencies.

In the subsequent sections, the methodology employed for feature selection, data preprocessing, model architecture design, and training strategy will be discussed in detail.

3.4 Exploratory Data Visualization

To gain preliminary insights into the behavior of the measured variables across a typical cycle, a visual analysis was conducted on the current, voltage, temperature, and discharge capacity profiles of a representative battery cell. Specifically, the first charge-discharge cycle of the first battery in the dataset was selected for this purpose.

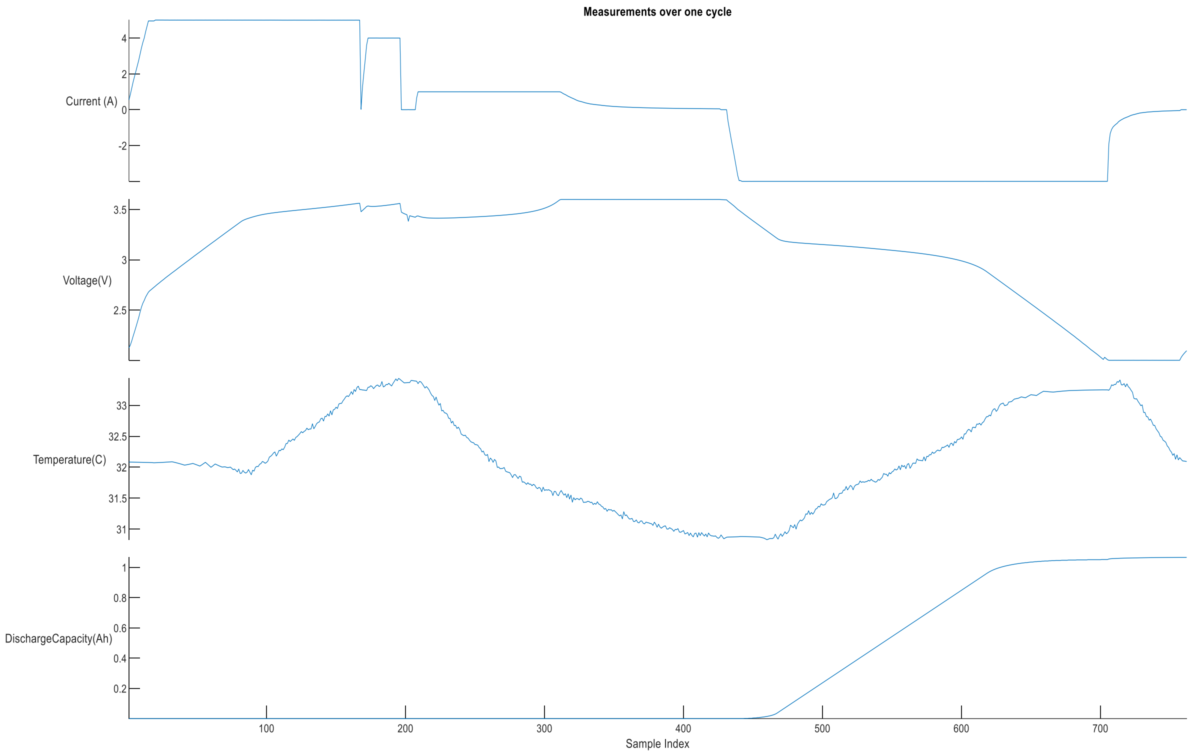

Figure (3.2): Measurements of discharge data for the first cycle of the first battery.

The plot reveals several key features:

- **Current behavior:** Positive current values correspond to the charging phase, whereas negative values indicate discharge. The distinction between these two phases is clearly demarcated within each cycle.
- **Voltage profile:** The cell voltage increases during charging and decreases during discharging. The terminal voltage reaches approximately 3.6 V at full charge and drops to around 2 V at full discharge, which aligns with standard lithium-ion battery operating ranges.

- **Thermal response:** The temperature exhibits moderate fluctuations over the course of the cycle, reflecting thermal coupling with the electrochemical processes.
- **Capacity tracking:** The discharge capacity is monitored throughout the cycle, serving as a critical metric for identifying degradation trends over time.

This preliminary visualization confirms the consistency and integrity of the recorded measurements and provides a foundation for subsequent stages of data preprocessing and feature extraction. Furthermore, it highlights the variability introduced by different fast-charging protocols applied across the dataset, which is a key factor influencing the degradation behavior and ultimately, the cycle life of each cell.

3.5 Extraction and Transformation of Discharge Cycle Data

Given the variability in charging protocols applied to different battery cells in the dataset, a consistent basis for comparison must be established. Although charging behavior differs widely, the **discharge voltage range** remains consistent across all cells. Consequently, this study focuses exclusively on the **discharge segments** of the charge-discharge cycles to ensure uniformity and comparability in the data analysis process.

To extract the relevant measurements corresponding to the discharge portion of each cycle, a custom data-handling routine (**hExtractDischargeData**) is employed. This function isolates key signals—voltage, temperature, and discharge capacity—recorded during the discharge phase. An illustrative stacked plot of these measurements for the first cycle of the first battery cell is shown in the figure, providing a clear depiction of the discharge profile over time.

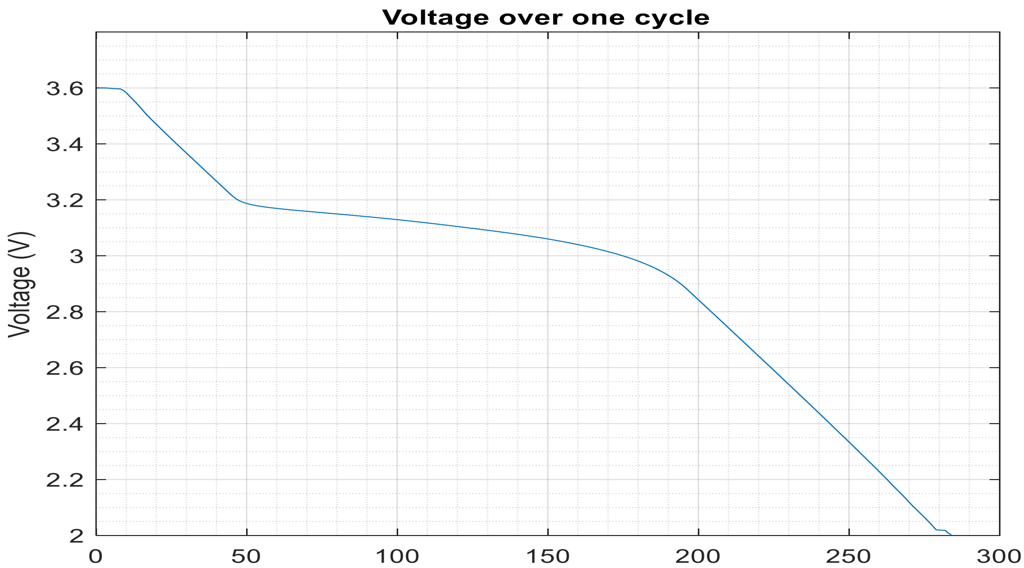

Figure (3.3): Measurements of voltage over one cycle

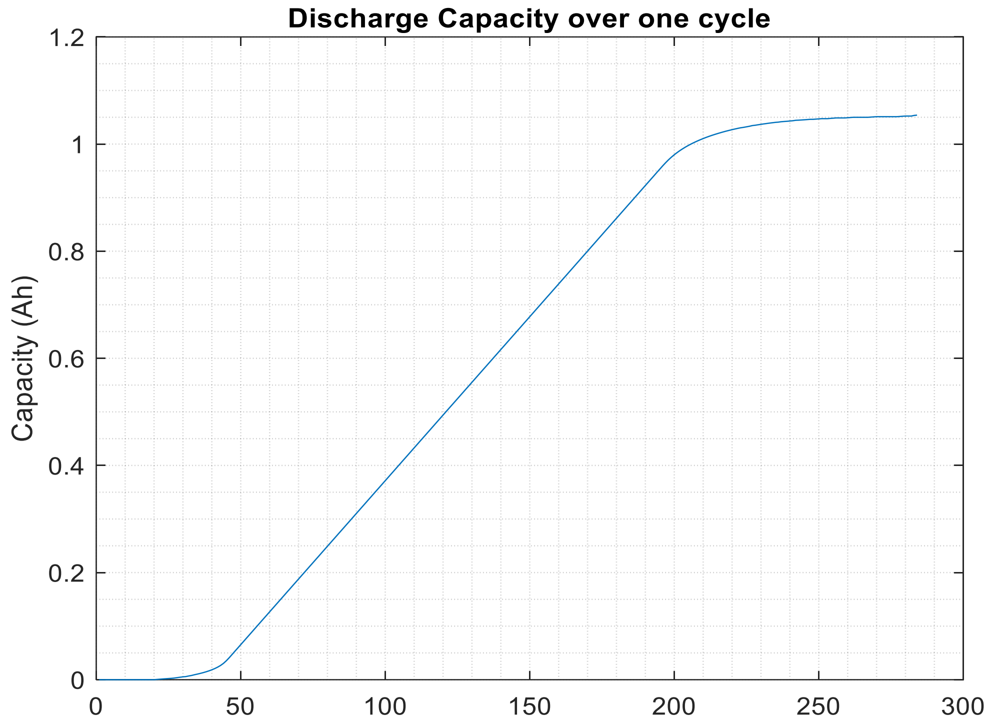

Figure (3.4): Measurements of discharge capacity over one cycle

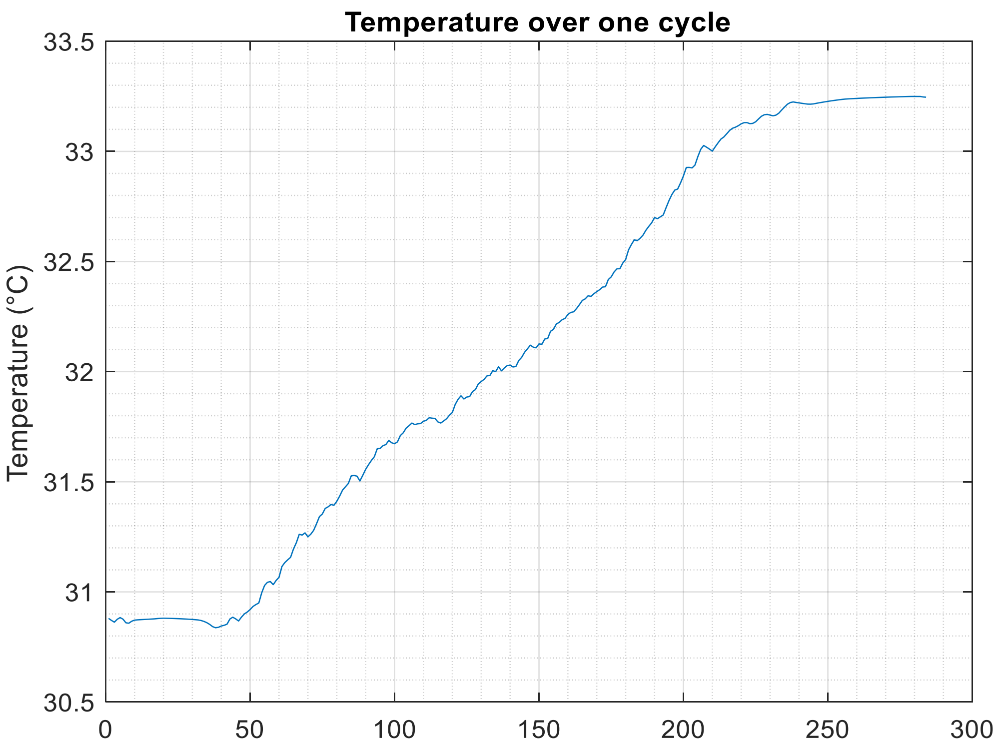

Figure (3.5): Measurements of temperature over one cycle

Notably, due to differing charging policies and load conditions, **the duration of individual discharge cycles varies significantly** among cells. As a result, direct temporal comparisons are unreliable. To address this, **voltage** is adopted as the reference domain instead of time. Since the voltage profile during discharge spans a consistent range (typically from 3.6 V down to 2.0 V), it provides a stable axis along which measurements can be aligned across all cells and cycles.

To standardize the data representation, voltage, temperature, and discharge capacity values are interpolated using a linear interpolation function (**hLinearInterpolation**).

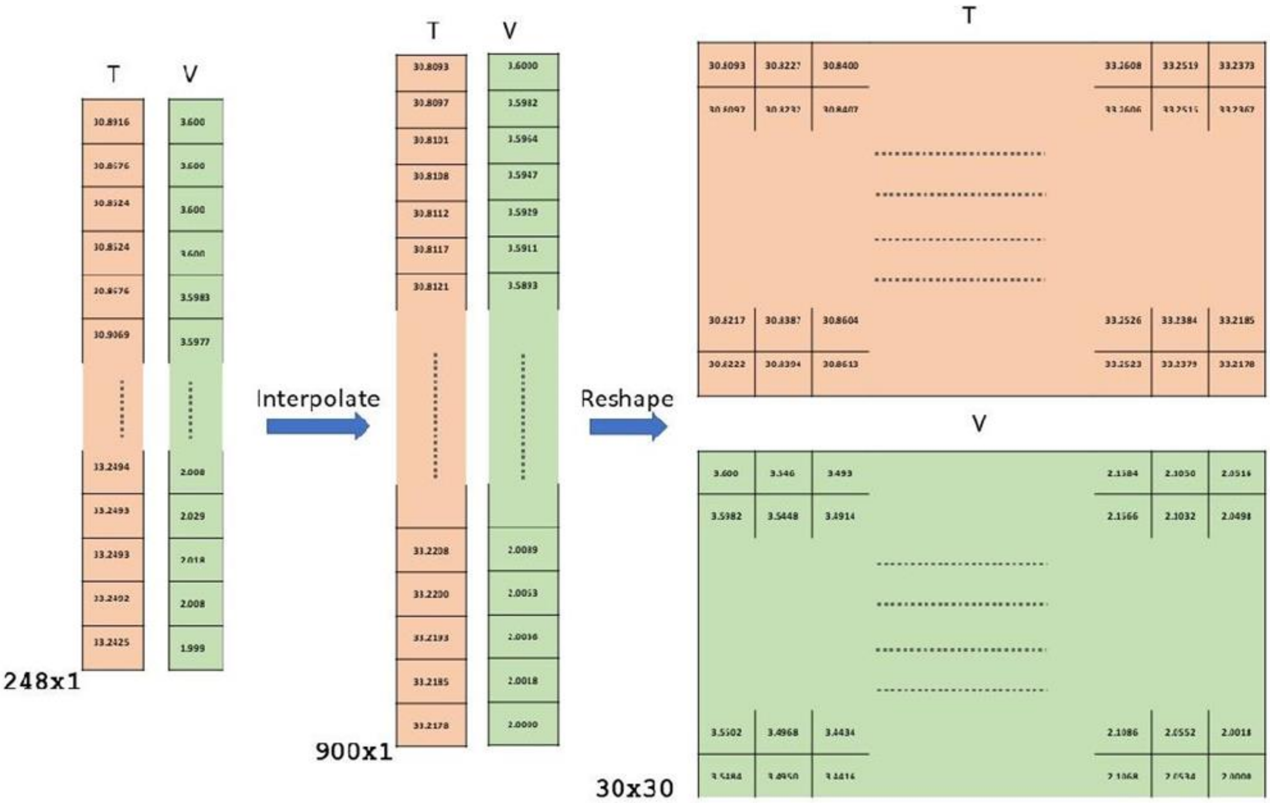

Figure (3.6): The interpolated temperature and discharge capacity as a function of voltage.

The interpolation is performed over a **uniformly sampled 900-point voltage range** between 3.6 V and 2.0 V. The resulting 900-dimensional vectors are then **reshaped into 30×30 matrices**, effectively converting the sensor data for each cycle into a two-dimensional spatial representation.

This transformation serves a dual purpose:

1. It enables consistent input dimensionality for training the deep learning model.
2. It allows convolutional layers in the network to explore **spatial correlations** across the interpolated measurements. While these correlations are not spatial in the physical sense, the structured 2-D format encourages the model to learn localized patterns that may correspond to characteristic degradation signatures.

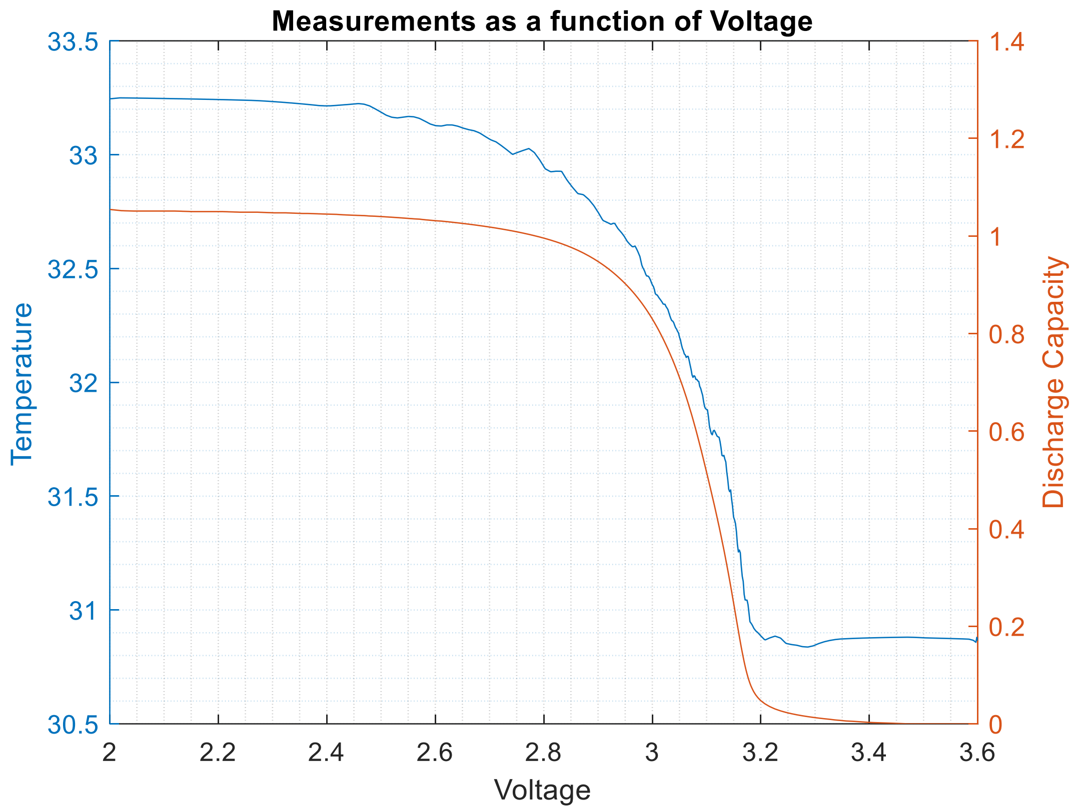

Figure (3.7): Measurements as a function of voltage

3.6 Data Formatting for Deep Learning Model

the interpolated discharge measurements for input into a deep learning framework, a composite representation is constructed by combining multiple sensor signals into a unified, structured format. Specifically, the interpolated temperature, discharge capacity, and voltage values for each battery cycle—originally each a one-dimensional vector of 900 points—are reshaped into 30×30 matrices, as previously discussed.[49]

These matrices are then **concatenated along a third dimension**, forming a three-dimensional array of size **30×30×3**. This configuration is analogous to the structure of an RGB image, where each channel represents a different signal modality. In this context:

- The first channel corresponds to interpolated **voltage** data,
- The second channel captures **discharge capacity**, and
- The third channel records **temperature**.

This multidimensional format allows convolutional neural network (CNN) layers to simultaneously process and extract spatially aligned features across all three modalities. The assumption underlying this approach is that localized patterns and interactions among voltage, temperature, and capacity may reveal latent indicators of degradation, which can be exploited to improve prediction accuracy.

To illustrate the nature of the interpolated input data, a plot of **temperature** and **discharge capacity** as functions of voltage is generated for a representative cycle (Figure 3.4, to be inserted). These plots confirm that the interpolation process preserves the structural integrity of the original signals, enabling consistent spatial representation across cycles.

In preparation for supervised learning, the expected output—i.e., the remaining useful life (RUL) in terms of cycle count—is normalized to ensure numerical stability during training. The normalization is performed by dividing the target values by **2000**, which corresponds to the approximate maximum cycle life observed in the dataset. This normalization bounds the output in the [0, 1] range, facilitating convergence during training.

To partition the data for model development, the dataset is divided as follows:

- **Training set:** 30 batteries
- **Validation set:** 5 batteries
- **Test set:** 5 batteries

This split ensures that the model is evaluated on unseen data representing batteries not involved in the training process, which is essential for assessing generalization performance.

Finally, the helper function hreshapeData is employed to generate the input-output pairs required for training the network. This function returns:

- train Data: a collection of 30×30×3 formatted matrices representing individual discharge cycles,
- trainRulData: the corresponding normalized RUL values serving as ground truth labels for supervised learning.

3.7 Deep Neural Network Architecture

Designing an effective convolutional neural network (CNN) for predicting battery cycle life involves careful selection of layer types, depth of the network, and configuration of associated hyperparameters. The objective is to achieve a favorable trade-off between model complexity, generalization capability, and computational efficiency during training and inference.[50]

In this study, the interpolated battery discharge measurements—comprising **voltage**, **temperature**, and **discharge capacity**—are treated as a three-channel input, analogous to the red, green, and blue (RGB) channels of a digital image. These inputs are normalized to the range [0,1][0,1][0,1] to ensure stable and consistent convergence during training.

The proposed network architecture is composed of the following successive layers:

- **Image Input Layer:**
  Accepts input data in the form of a 30×30×3 tensor, where the three channels represent voltage, temperature, and capacity, respectively. Normalization of input values is incorporated to reduce internal covariate shift and facilitate smoother gradient flow during backpropagation.

- **2-D Convolutional Layers:**

  A total of **four convolutional layers** are employed in the network. Each layer applies a series of learnable filters over the input or feature maps, enabling the extraction of local spatial features relevant to degradation patterns. The number of convolutional layers was determined empirically through iterative experimentation, balancing predictive performance with computational cost.

- **Layer Normalization Layers:**

  Following each convolutional layer, a **layer normalization** step is applied. This technique standardizes the activations within each layer, accelerating the training process and enhancing the model's robustness to weight initialization.

- **ReLU Activation Layers:**

  Each normalization layer is followed by a **rectified linear unit (ReLU)** activation function. ReLU introduces nonlinearity into the network by applying an element-wise thresholding operation, which enhances the model's capacity to learn complex nonlinear relationships.

- **Pooling Layers:**

  To reduce spatial dimensionality and suppress redundant information, **pooling layers** are inserted after the first two ReLU layers. These layers downsample the feature maps, thereby decreasing the number of trainable parameters and mitigating overfitting while retaining the most salient features.

- **Fully Connected Layer:**

  Finally, the deep feature maps are passed through a **fully connected layer**, which consolidates the extracted features and maps them to a single scalar output—representing the **normalized remaining cycle life** of the battery. This architecture effectively exploits the multi-dimensional nature of the input data, allowing the network to detect abstract patterns that correlate with aging behaviors and remaining useful life. Subsequent sections will describe the training methodology, including loss function selection, optimization strategies, and performance evaluation.[51]

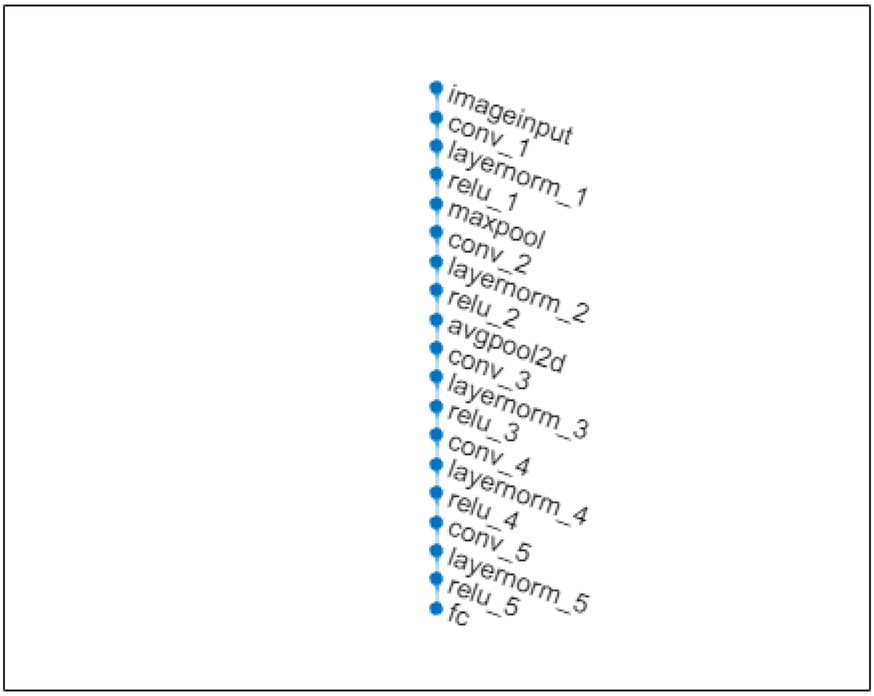

Figure (3.8): the architecture of convolutional neural network

3.8 Network Hyperparameter Configuration and Training Strategy

Following the definition of the network architecture, the next critical step involves specifying the **training strategy**, particularly the selection and tuning of **hyperparameters**. These parameters govern the learning process and significantly influence the convergence behavior, training efficiency, and final predictive performance of the model. Due to the highly empirical nature of deep learning, hyperparameter tuning is typically conducted through **iterative experimentation** and informed heuristics.

For this study, the **Adam optimizer** (Adaptive Moment Estimation) is employed. Adam is widely recognized for its computational efficiency and robustness across a broad range of deep learning tasks. It combines the benefits of both AdaGrad and RMSProp by maintaining adaptive learning rates for each parameter and incorporating momentum, making it well-suited for problems with noisy gradients or sparse data.

The training configuration is defined as follows:

- **Optimizer:** Adam

  The Adam solver is chosen for its fast convergence, low sensitivity to hyperparameter initialization, and minimal manual tuning requirements.

- **Mini-Batch Size :** 256
  A mini-batch size of 256 samples is used. This value balances computational efficiency with the gradient estimation stability needed for effective learning.
- **Number of Epochs :** 50

  The model is trained for 50 full passes over the training dataset. This number of epochs was found to provide adequate convergence without inducing overfitting.
- **Data Shuffling:** Enabled (per Epoch)

  To ensure that the model generalizes well and to prevent the network from learning spurious patterns in data order, the dataset is shuffled prior to each epoch.
- **Initial Learning Rate:** 0.001

  An initial learning rate of 0.001 is selected, representing a compromise between convergence speed and the risk of divergence. This value enables the optimizer to make meaningful progress during early iterations without overshooting local minima.
- **Validation Strategy:** Periodic Validation

A validation subset is used to periodically evaluate the model's performance during training. This process serves as an early warning mechanism for overfitting and provides insight into the network's generalization behavior.

The chosen values for these hyperparameters are derived through a series of trial-and-error experiments. Although they yield satisfactory results in this study, they remain open to further tuning depending on model performance and available computational resources.

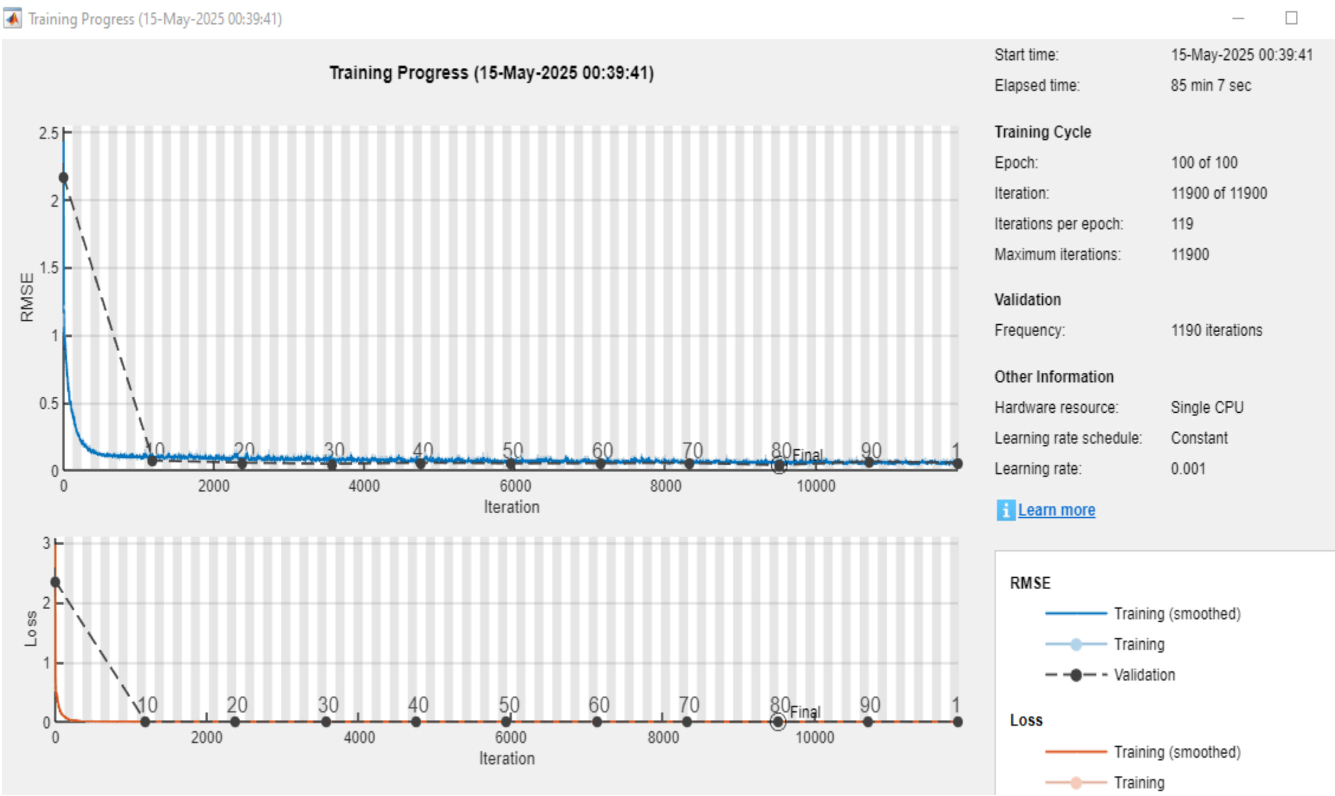

Figure (3.9): training progress model

3.9 Evaluation of Model Performance

Following the training process, it is essential to evaluate the predictive accuracy and generalization capability of the developed convolutional neural network. In this phase, the trained model is applied to the previously reserved test dataset, which was not used during the training or validation stages.

To interpret the results in terms of the actual number of cycles, the predicted values are rescaled to the original range of the **Remaining Useful Life (RUL)** by multiplying the normalized predictions by the factor used during preprocessing. In this study, the maximum cycle life was normalized by a factor of 2000; therefore, post-inference scaling is applied accordingly.

A scatter plot is then generated to visually compare the **predicted cycle life** with the **actual cycle life** from the test set

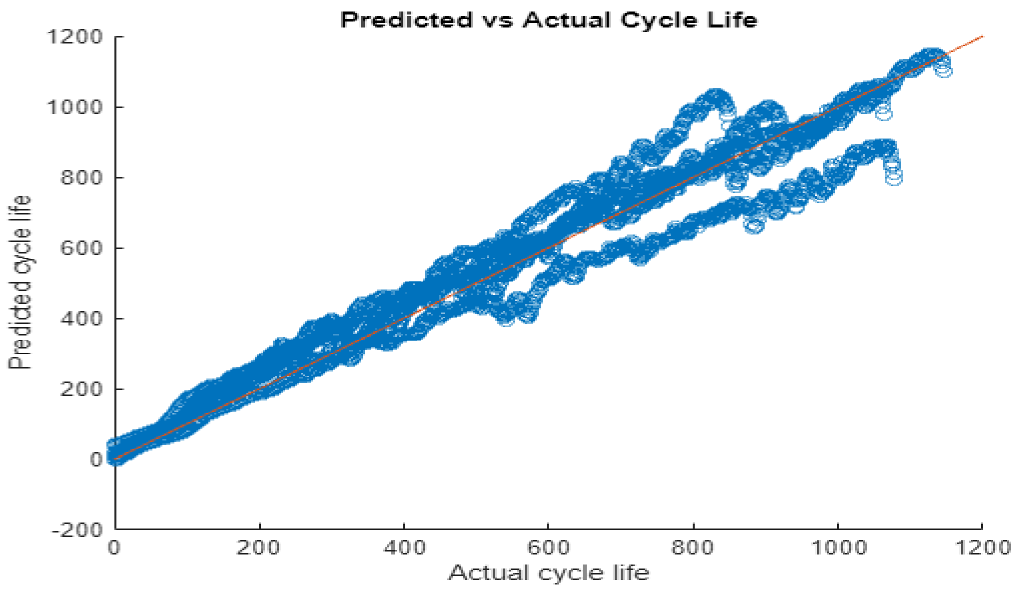

Figure (3.10): Compare the actual cycle life with the predicted cycle life

This plot provides an intuitive visual indication of the model's performance. The proximity of the data points to the **diagonal reference line** (slope = 1) reflects how accurately the model is able to predict battery lifespan. Deviations from this line suggest discrepancies between the actual and predicted values.

The overall distribution of points around the reference line can also indicate potential biases, such as systematic underestimation or overestimation of battery life in certain cycle ranges. Such insights are critical for assessing the practical deployment of the model in real-world battery health monitoring applications.

Further quantitative performance analysis may be conducted using statistical metrics such as the **Root Mean Square Error (RMSE)** or **Mean Absolute Error (MAE)** to complement the graphical analysis presented.

3.10 Model Evaluation and Interpretation

The performance of the trained convolutional neural network model was evaluated using the previously reserved test dataset. The predicted remaining cycle life values were scaled back to the original range using the inverse of the normalization factor applied during preprocessing (i.e., multiplied by 2000). A scatter plot was generated to visually compare the predicted cycle life with the actual values.

In an ideal scenario, the predicted values would align closely with the diagonal reference line (slope = 1), indicating perfect predictions. However, the scatter plot reveals a broader dispersion around the diagonal, indicating varying degrees of prediction accuracy across the dataset.

Upon visual inspection, five distinct trends can be observed in the scatter plot—each corresponding to a different battery in the test set. The following insights can be derived from this observation:

- **High Accuracy at End-of-Life:** For lower actual cycle life values (i.e., near the end of a battery's life), the model predictions tend to be more accurate and closely follow the ideal diagonal. This suggests that the model is particularly effective at estimating the remaining useful life (RUL) when a battery approaches failure.
- **Greater Uncertainty at Early Life:** For higher actual cycle life values (i.e., early in the battery’s operational life), the model exhibits increased prediction uncertainty and a tendency to **overestimate** the remaining life. This can be attributed to the reduced variability in sensor signals during the early stages of degradation, making it more difficult for the model to differentiate between healthy batteries.
- **Prediction Spread and Model Limitations:** The noticeable spread in predictions across the five batteries highlights a limitation in generalization and suggests the need for a more diverse and comprehensive training dataset. Additionally, architectural enhancements and hyperparameter tuning may further improve performance.

The obtained values are:

Mean Absolute Percentage Error (MAPE): 18.84%

These results are comparable to those obtained in conventional machine learning-based methods, such as regularized linear regression models trained on handcrafted features. However, unlike those methods which require feature engineering and typically rely on the first 100 cycles of data, the deep learning model in this study can utilize data from **any point** in the battery life cycle. This flexibility is a significant advantage in practical deployment scenarios.

Finally, once satisfactory performance is achieved, the trained network can be deployed for real-time battery health monitoring. For embedded systems, the model can be converted into **C/C++**, **GPU**, or **HDL** code using MATLAB's code generation tools. For cloud deployment, packaging options can be chosen based on the intended platform and application requirements.

3.11 Conclusion

This chapter transitioned from theoretical framework to practical implementation, presenting a custom-designed convolutional neural network tailored for the prediction of lithium-ion battery capacity and cycle life. The design process was guided by insights from both battery degradation physics and deep learning theory, resulting in an architecture that integrates domain-specific knowledge with data-driven modeling strategies.

The model ingests a three-channel input tensor comprising normalized voltage, temperature, and capacity signals across charge-discharge cycles. This structure allows the CNN to treat the temporal evolution of battery states as a spatial learning problem, leveraging convolutional kernels to extract degradation patterns and operational trends. The network architecture was carefully constructed with multiple convolutional blocks, interleaved with activation functions (ReLU), batch normalization layers, and max-pooling operations to balance complexity with generalization capability. A final fully connected layer translates the high-level feature map into a cycle life prediction, completing the regression task.

Training was conducted using the Adam optimizer and mean squared error loss function, with empirical tuning of hyperparameters such as learning rate, batch size, and number of epochs to enhance convergence and prevent overfitting. The model's performance was validated using real-world test data, with evaluation metrics and scatter plots demonstrating its ability to capture non-linear degradation behaviors with reasonable accuracy. The results affirm the model's potential to serve as a predictive tool in battery management systems (BMS), offering early warnings of capacity fade and supporting optimal usage strategies.

Overall, this chapter demonstrates that the integration of CNNs into battery diagnostics is not merely a computational exercise but a meaningful contribution to the broader effort of making energy storage systems smarter, more efficient, and more reliable. The implementation insights and performance outcomes presented here provide a solid basis for further development, including potential adaptations to other battery chemistries, integration with real-time embedded systems, and extension into hybrid modeling approaches.

General Conclusion

The accurate prediction of battery life cycles has become increasingly critical in modern energy storage applications, particularly with the rapid proliferation of electric vehicles, renewable energy systems, and portable electronics. Ensuring battery reliability, optimizing maintenance schedules, and minimizing operational costs all hinge on a robust estimation of the Remaining Useful Life (RUL) of battery cells. This thesis has addressed this significant challenge by exploring the integration of deep learning—specifically convolutional neural networks (CNNs)—to predict the life cycle of lithium-ion batteries using voltage, temperature, and discharge capacity data.

The work commenced with a comprehensive review of the theoretical background of battery degradation mechanisms and conventional methods for estimating battery life. Limitations inherent in traditional and shallow machine learning techniques, such as the need for extensive feature engineering and restricted adaptability to new data, were outlined. These constraints motivated the exploration of deep learning methodologies, which offer an end-to-end learning capability that automatically captures hidden patterns within raw multivariate time-series data.

A key component of this study was the use of a curated NASA battery dataset, which was preprocessed and interpolated to generate uniform 30×30 matrices representing voltage, capacity, and temperature measurements across charge-discharge cycles. These matrices were treated analogously to RGB image channels, thereby making them amenable to 2D CNN processing. The data were partitioned into training, validation, and testing subsets drawn from 40 individual battery cells to ensure model generalizability and prevent overfitting.

The network architecture was carefully designed, consisting of successive convolutional, normalization, activation (ReLU), pooling, and fully connected layers. The choice of layer depth and structure was based on empirical experimentation, balancing predictive performance with training efficiency. Hyperparameter selection—such as batch size, learning rate, optimizer (Adam), and validation strategy—was similarly optimized through iterative testing.

MATLAB's Deep Learning Toolbox provided the computational framework for model training and evaluation. The model demonstrated an ability to capture degradation signatures and predict the RUL with a **Root Mean Squared Error (RMSE) of approximately 71.4 cycles** and an **average percentage error of 18.84%**. These results are competitive with traditional machine learning benchmarks, with the added benefit of scalability, robustness to feature variability, and real-time applicability.

Visualization of the model's predictions through scatter plots revealed important behavioral patterns. The CNN showed higher confidence and accuracy in predicting battery life at later stages of degradation—when observable features become more distinct. Conversely, during early stages of battery usage, where degradation signals are subtle, the model tended to overestimate RUL. This limitation highlights a general challenge in predictive modeling of time-dependent systems and points to avenues for future improvement.

From a broader perspective, this thesis contributes to the growing body of evidence supporting the viability of deep learning in battery health diagnostics. The results demonstrate that CNNs, when properly trained and architected, can yield meaningful predictions without the need for manually engineered features. Moreover, this approach is well-suited for deployment in embedded systems and cloud platforms, enabling real-time health monitoring and predictive maintenance.

Recommendations for Future Work

While the outcomes of this study are promising, several directions for future research are worth pursuing:

- **Data Diversity and Quantity:** Incorporating a more diverse dataset that includes different battery chemistries, usage patterns, and environmental conditions could significantly enhance model generalizability.
- **Hybrid Architectures:** Combining CNNs with recurrent neural networks (e.g., LSTM or GRU layers) may better capture temporal dependencies in battery degradation processes.
- **Uncertainty Quantification:** Introducing probabilistic modeling or Bayesian deep learning approaches could provide confidence intervals around predictions, enhancing reliability in safety-critical applications.
- **Explainability and Interpretability:** Methods such as saliency maps or SHAP values can be integrated to interpret model behavior and offer insights into the physical meaning of learned features.
- **Real-Time Deployment:** Investigating hardware-specific optimizations for deploying trained models on edge devices (e.g., microcontrollers or FPGAs) could enable commercial implementation in smart battery management systems.

Final Remarks

This thesis has demonstrated a comprehensive and technically sound approach to predicting battery life cycles using convolutional neural networks. By leveraging deep learning's power to autonomously extract features from complex multivariate data, this work moves a step closer to realizing intelligent battery management systems that are adaptive, predictive, and operationally efficient. The implications span across numerous industries and applications, reaffirming the transformative role of artificial intelligence in the future of energy storage and sustainability.

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