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Review

State of the Art in Electric Batteries' State-of-Health (SoH) Estimation with Machine Learning: A Review

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Abstract: The sustainable reuse of batteries after their first life in electric vehicles requires accurate state-of-health (SoH) estimation to ensure safe and efficient repurposing. This study applies the systematic ProKnow-C methodology to analyze the state of the art in SoH estimation using machine learning (ML). A bibliographic portfolio of 534 papers (from 2018 onward) was constructed, revealing key research trends. Public datasets are increasingly favored, appearing in 60% of the studies and reaching 76% in 2023. Among 12 identified sources covering 20 datasets from different lithium battery technologies, NASA's Prognostics Center of Excellence contributes 51% of them. Deep learning (DL) dominates the field, comprising 57.5% of the implementations, with LSTM networks used in 22% of the cases. This study also explores hybrid models and the emerging role of transfer learning (TL) in improving SoH prediction accuracy. This study also highlights the potential applications of SoH predictions in energy informatics and smart systems, such as smart grids and Internet-of-Things (IoT) devices. By integrating accurate SoH estimates into real-time monitoring systems and wireless sensor networks, it is possible to enhance energy efficiency, optimize battery management, and promote sustainable energy practices. These applications reinforce the relevance of machine-learning-based SoH predictions in improving the resilience and sustainability of energy systems. Finally, an assessment of implemented algorithms and their performances provides a structured overview of the field, identifying opportunities for future advancements.

Keywords: state of health; battery; machine learning; ProKnow-C; public datasets; energy informatics; smart grids; internet of things; deep learning

Academic Editor: Jose Luis Calvo-Rolle

Received: 13 January 2025
Revised: 31 January 2025
Accepted: 4 February 2025
Published: 6 February 2025

Citation: Sylvestrin, G.R.; Maciel, J.N.; Amorim, M.L.M.; Carmo, J.P.; Afonso, J.A.; Lopes, S.F.; Ando Junior, O.H. State of the Art in Electric Batteries' State-of-Health (SoH) Estimation with Machine Learning: A Review. *Energies* **2025**, *18*, 746. https://doi.org/10.3390/en18030746

1. Introduction

The worldwide increase in battery usage is evident in various fields, especially in electric vehicles. Research efforts aim to improve battery efficiency, extend lifespan, and reduce charging time, driven by the demands of a growing global market. Alongside advancements in technology, vehicle battery reuse has emerged as a key area of focus. Batteries can serve automotive purposes until their capacity drops to about 80% of the nominal value. Beyond this point, replacement is necessary to meet the power requirements of vehicles [1]. However, the cells from these batteries can still be repurposed for other applications, such as stationary energy storage systems connected to photovoltaic generation devices. This process, known as second use, offers a sustainable way to extend battery life.

The repurposing of a second-use battery is still a process that requires improvement because of construction and safety difficulties. Accurate estimation of batteries' SoH is pivotal in advancing sustainable energy solutions. By integrating SoH predictions into smart grids and IoT systems, it is possible to optimize energy management, enhance system resilience, and reduce waste, aligning with broader energy informatics and sustainability goals. With increasing computational advances, the presence of smart sensors, and the era of big data, there has been growing research interest in applying machine-learning (ML) algorithms of artificial intelligence [2–4]. Accurate SoH characterization is essential for assessing cells suitable for reuse. As new datasets become available, the volume of research connecting ML to SoH estimation continues to grow, as demonstrated by numerous recent studies [5–9].

The estimation of the SoH of batteries is a critical step for enhancing their lifecycle management, especially in applications where reliability and performance are paramount [1]. Commonly employed methods for SoH estimation can be broadly classified into electrochemical approaches and model-based, data-driven, and hybrid methods [10–13]. Electrochemical approaches, although less common in operational environments because of their invasive nature, offer unparalleled precision for understanding battery degradation mechanisms. For instance, differential voltage analysis and differential capacity analysis [14,15] are used to track specific aging signatures by analyzing voltage–capacity profiles during charge/discharge cycles. These methods, combined with techniques like cyclic voltammetry [16] or advanced electrochemical impedance spectroscopy [17], provide detailed insights into phenomena such as lithium plating and active material loss. Although such methods are typically applied in laboratory settings, recent advances in sensor technology and signal processing aim to make them more feasible for real-time SoH estimation [15].

Model-based methods rely on electrochemical or equivalent-circuit models to predict the SoH by capturing the physical and chemical behaviors of the battery [18]. Techniques such as electrochemical impedance spectroscopy [19], Kalman filtering [18], and particle filtering [20] are widely used in this category. These methods offer precise insights into battery performance but often require complex parameter tuning and are computationally intensive [18,20].

Data-driven methods, on the other hand, utilize ML and DL algorithms to analyze large datasets and uncover patterns indicative of battery degradation [10]. These methods excel in modeling nonlinear relationships and adapting to diverse battery chemistries and usage patterns [10,11]. However, their reliance on large amounts of labeled data and challenges in interpretability limit their direct application in some scenarios [10,11,13]. Hybrid methods combine the strengths of model-based and data-driven approaches, leveraging physical models to enhance the interpretability and robustness of ML-based predictions. In [21,22], hybrid approaches integrating equivalent-circuit models with ML techniques are proposed, achieving a balance between accuracy and computational complexity. Despite their promise, hybrid methods often require significant domain-specific expertise and extensive computational resources [23].

Recent advancements in computational power and the availability of large datasets have significantly boosted the prominence of data-driven methods, making them a cornerstone in SoH estimation for large-scale applications, like electric vehicles and stationary energy storage systems [10,11]. Nonetheless, challenges persist regarding data availability, algorithmic generalization, and system interpretability [13].

The work presented in [10] provides a list of advantages and disadvantages of using ML algorithms, highlighting the need for open platforms for data sharing and modeling techniques as a necessary step for the advancement of the research field. In the context of challenges and prospects, studies [24–26], which focus on exploring DL techniques for estimating the remaining battery life, are also noteworthy, while in [27], this theme is reviewed from the perspective of transfer-learning usage. In [28], challenges and prospects are addressed considering the importance of feature extraction, construction, and selection for health state modeling. The importance of battery health characterization is presented in [12], under the challenges of scaling second-use batteries. In [11], a relevant review of state-of-charge (SoC) and -health estimation is presented, where the authors reveal comparative results mainly considering neural networks, such as feedforward neural networks (FFNNs), recurrent neural networks (RNNs), and long short-term memories (LSTMs). Studies [29–31] also provide a review focused on comparing techniques for studying battery degradation. In all the relevant review papers in recent years that have been analyzed, a common gap can be pointed out: the absence of a structured methodology that underpins the analysis portfolio and leads to the authors' conclusions.

Although significant research has been conducted on data-driven algorithms for SoH estimation, systematic methodologies are lacking to ensure the selection of highly relevant studies for constructing a reliable state-of-the-art overview. The absence of such approaches makes it difficult to identify emerging trends in the field. In this context, and given the relevance of the topic, this work aims to explore the recent state-of-the-art panorama, from the last 5 years, for the estimation of batteries' SoHs. To achieve this, we start with the explanation and demonstration of a structured and systematic methodology, known as ProKnow-C (Knowledge Development Process Constructivist) [32], to obtain a centralized bibliographic portfolio on the topic of predicting the health states of batteries, using ML. ProKnow-C is a structured process designed to assist researchers in systematically identifying, selecting, and analyzing a bibliographic portfolio aligned with their research objectives [32–34]. It stands out as a comprehensive approach for conducting literature reviews because it combines quantitative and qualitative criteria, ensuring the inclusion of highly relevant and impactful studies while minimizing biases often present in manual selection processes [32,35]. By applying this methodology, we aim to construct a robust bibliographic portfolio that provides a reliable foundation for evaluating the state of the art in batteries' SoH estimations. In this way, this paper's contributions are summarized as follows:

Application of the ProKnow-C Methodology: The presentation and demonstration of the ProKnow-C systematic methodology for building a bibliographic portfolio. This systematic approach allows for rigorous and structured literature reviews.

Characterization of the Research Scenario (State of the Art): Characterization of the current scenario of studies in the health-state estimation of batteries, using ML by analyzing 534 relevant articles published between 2018 and 2024. This provides a comprehensive state of the art in the current research field.

Public Dataset Compilation: Presentation, detailing, and summary of 20 public datasets from 12 different sources, primarily from university research centers, for selecting suitable datasets for research in SoH, SoC, and battery energy storage systems.

Machine-Learning and Deep-Learning Algorithms: Research of the main ML algorithms used in studies predicting response variables related to battery degradation, including deep-learning, hybrid, and transfer-learning models.

Performance Analysis of SoH Estimation Models: A comprehensive performance analysis of state-of-health estimation models, focusing on various response variables, including SoH, remaining-useful-life, current-lifecycle, capacity, trajectory, and early-useful-life predictions. The comparison involves 21 studies, allowing for both fair and broader comparisons.

First Study Applying ProKnow-C to Batteries' SoHs: This study is the first to apply the ProKnow-C systematic review method in the context of batteries' state-of-health estimations. This pioneering application sets a new standard for structured literature reviews in this field.

The remainder of this paper is organized as follows: Section 2 details a systematic review using the ProKnow-C methodology, enabling rigorous and structured literature selection, mapping the state of the art in studies and experiments and available open datasets for the applicability of these techniques. Section 3 discusses in detail the content analysis of the bibliographic review, as well as the analyses of the papers composing the bibliographic portfolio on this topic, including the main databases and ML algorithms, along with the key literary studies. Additionally, this section explores the potential practical applications of SoH estimation in energy informatics, smart grids, and IoT systems, highlighting its role in enhancing energy efficiency, sustainability, and operational resilience. Finally, Section 4 offers concluding remarks, summarizes the main results, and provides suggestions for future research, exploring potential developments based on the integration of artificial intelligence in various scenarios while identifying gaps and opportunities for future research.

2. Systematic Review

The adoption of systematic processes for bibliographic surveying allows for optimizing the quality of the material obtained on a particular topic, as it makes the process more analytical and rigorous, thereby improving the reliability of the results found. As this is an initial and fundamental stage for all research development, methods that increase the robustness of a bibliographic portfolio are essential [36].

In this paper, the systematic method ProKnow-C is employed to obtain a recent and scientifically relevant bibliographic portfolio on the use of ML in estimating SoHs of batteries. ProKnow-C was developed at the Laboratory of Multicriteria Methodologies in Decision Support (LabMCDA) at the Federal University of Santa Catarina (UFSC) and patented in 2010 [32]. This method has been applied in research in various areas, and some examples of ProKnow-C applications can be observed in [33,35,36].

Within the field of electric batteries, the ProKnow-C method was applied in [34] to define the state of the art in lithium-ion-battery recycling. Although related, the present study specifically focuses on analyzing the state of the art in SoH estimation using ML methods. To date, no similar study applying ProKnow-C has been observed.

The ProKnow-C method consists of four main stages [36]:

- Selection of a portfolio of papers on the research topic: This involves defining research keywords, searching in databases, and filtering articles based on alignment with the research objective, citation metrics, and relevance;
- Bibliometric analysis of the portfolio: This stage examines scientific indicators, such as the number of articles, citation counts, authors, and journals, to assess the portfolio's comprehensiveness and scientific impact;
- Systemic analysis: The selected articles are deeply analyzed for insights and patterns and the identification of possible research gaps;

- Definition of the research question and objective: The results from the previous stages are synthesized to refine the scope and formulate precise research questions and objectives.

This paper presents the results of the first three stages of the ProKnow-C method, along with the analysis of the selected relevant papers. These stages represent a comprehensive state-of-the-art review of the broader research field, serving as a basis for refining the focus to a more specific and well-defined niche.

Other well-known systematic review methods can be found in the literature and may be used as alternatives to ProKnow-C. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [37] emphasizes transparency and replicability through strict adherence to predefined inclusion and exclusion criteria, making it widely regarded as a gold standard in fields such as energy systems, environmental science, artificial intelligence, and other technical domains [38–40]. However, PRISMA does not include a bibliometric evaluation phase or tools for multicriteria decision-making, which are central to ProKnow-C. Similarly, SALSA (Search, Appraisal, Synthesis, and Analysis) [41] focuses more on synthesizing and analyzing evidence but lacks the portfolio alignment capabilities of ProKnow-C, which ensures a targeted and relevant selection of articles. Another method, Scoping Reviews, is designed to map the breadth and depth of the literature on a topic, making it well-suited for exploratory studies or identifying gaps in the literature [42]. Although Scoping Reviews provides a broad overview, it is less structured in terms of bibliometric evaluation and often does not employ multicriteria tools to refine the portfolio, which are key strengths of ProKnow-C [43].

However, as with any method, ProKnow-C has its limitations. The subjective alignment analysis stage, although useful for tailoring the portfolio to specific objectives, may reduce repeatability [35]. Additionally, its reliance on citation metrics might overlook emerging but seldom-cited studies [35].

2.1. Bibliographic Portfolio Selection

This section describes the selection of the bibliographic portfolio, initially, the set of axes and keywords that encompass the theme of this research, i.e., the use of ML in estimating SoH, was defined. As shown in Table 1, axis 1 corresponds to the study object, which is batteries. Axes 2 and 3 encompass terms related to the definition of SoH and its estimation, respectively. Axis 4 includes terms related to artificial intelligence algorithms, machine learning, deep learning, and ensembles.

Table 1. Research axes for the bibliographic portfolio selection.

Axis 1	Axis 2	Axis 3	Axis 4
battery	state of health	estimation	machine learning
	cycle life	prediction	neural network
	lifetime	features	transfer learning
	aging	second use	artificial intelligence
	degradation		boosting
	useful life		quantile regression
			ensemble
			deep learning

The axes were combined using the conditional logic AND, resulting in 192 combinations searched in the Scopus database. Filters were established for documents of the types of papers and reviews, searching for the keywords in titles, keywords, and abstracts, as well as defining a research horizon of publications of up to 5 years old. The Scopus database was selected because of the larger volume of papers returned compared to other databases, such as Web of Science, as well as the presence of journals focused on areas possibly related to the research. An example of a condition resulting from the combination of axes was (TITLE-ABS-KEY(battery) and TITLE-ABS-KEY(state of health) and TITLE-ABS-KEY(prediction) and TITLE-ABS-KEY(neural network) and PUBYEAR > 2017 and (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re")).

Table 2 presents the adherence metrics for the keywords used in the combinations of axes. The percentages shown quantify the portions of the total number of raw articles in which a particular keyword was included in the performed combinations. Within axis 2 combinations, a higher adherence rate to the term "state of health" is observed, while in axis 3 and 4 combinations, the keywords "prediction" and "neural network" stand out, respectively. These adherence metrics suggest that within the theme of research related to battery's state of health, the term "state of health" tends to be more applied, often in connection with "prediction" studies utilizing "neural networks". It is important to note that although some terms show low adherence rates, they remain relevant for identifying potentially important papers that may explore emerging trends in an area of research still underexplored.

Table 2. Adherence to the research axes.

Axis	Keyword	Keyword Adherence Rate
Axis 2	state of health	29.3%
	degradation	20.6%
	aging	17.7%
	useful life	13.6%
	cycle life	10.9%
	lifetime	7.9%
Axis 3	prediction	36.5%
	estimation	30.9%
	features	24.9%
	second use	7.8%
Axis 4	neural network	36.9%
	machine learning	28.6%
	deep learning	14.6%
	ensemble	6.2%
	transfer learning	5.5%
	artificial intelligence	4.5%
	boosting	3.4%
	quantile regression	0.3%

This search was conducted on 14 January 2024, resulting in a total of 6032 papers (with 275 papers from 2024). Although there were papers from 2024, for the calculation of a publication horizon of up to 5 years, research from 2018 onward was considered, thus having 6 complete years of publications for analysis plus two weeks of publications in 2024. The papers were exported in ".csv" format in each iteration of the 192 combinations of axes.

The initial flow proposed by ProKnow-C is presented in Figure 1. The objective of this first stage is to significantly reduce the volume of papers in the RPD (raw paper database) obtained from the combinations of research axes. To achieve this, filters are applied to perform a preliminary selection of articles related to the research theme. The following filters are applied:

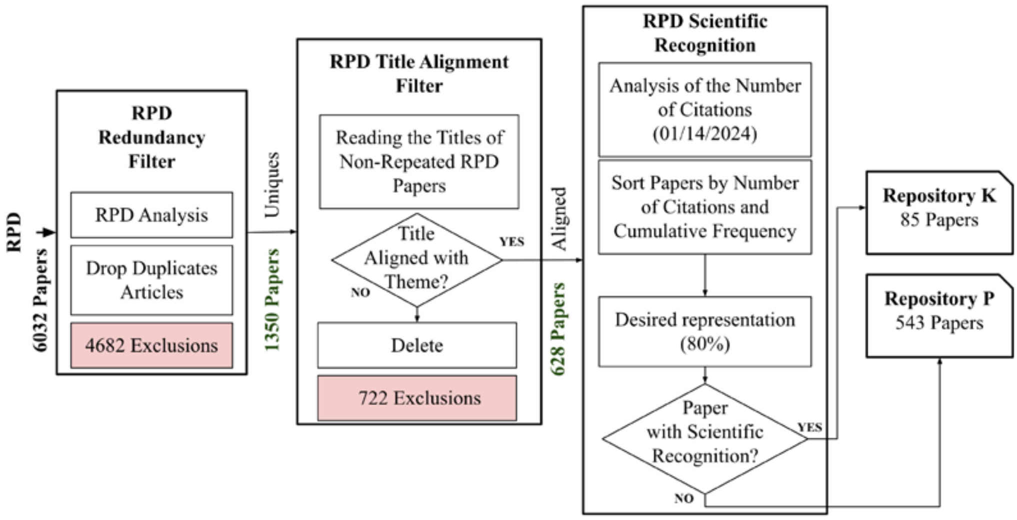


Figure 1. Flow I for obtaining the bibliographic portfolio.

Redundancy Filter: This is the first step of ProKnow-C, where the RPD papers are analyzed for duplication. In this stage, the ".csv" files resulting from the axis combinations were processed through a Python script that performed concatenation and removal of duplicates according to the title and publication year fields. A total of 4682 samples were removed from the RPD.

Title Alignment Filter: This involves reading the papers' titles to assess whether they are aligned with the research theme, as identified by the researchers. Out of the 1350 papers remaining after the previous filter, 722 were deemed to be not aligned with the research. Among the papers not selected were studies focused on SoH analysis in electrochemical contexts and laboratory experimental phases, which are considered as preliminary steps before exploring databases and implementing ML models.

Scientific Recognition Filter: This step involves analyzing the number of citations within the RPD. In this step, the remaining 672 papers are sorted in descending order by citation count. According to the cumulative percentage of citations and a predefined cutoff percentage, the portfolio is divided into two repositories: K and P. The K repository consists of papers considered as scientifically recognized, containing 80% of the citations in the input portfolio for this filter, totaling 85 publications in the case study. The cutoff percentage is determined by the researchers, with [32,36] recommending a range between 70% and 90%. The P repository comprises 543 papers exceeding the defined cutoff threshold.

The second flow of article selection steps for the bibliographic portfolio, using ProKnow-C, is presented in the flowchart in Figure 2. In this second phase of the method, the objective is to verify the alignment of the papers remaining from the first phase with the content presented in their abstracts. The following steps are applied:

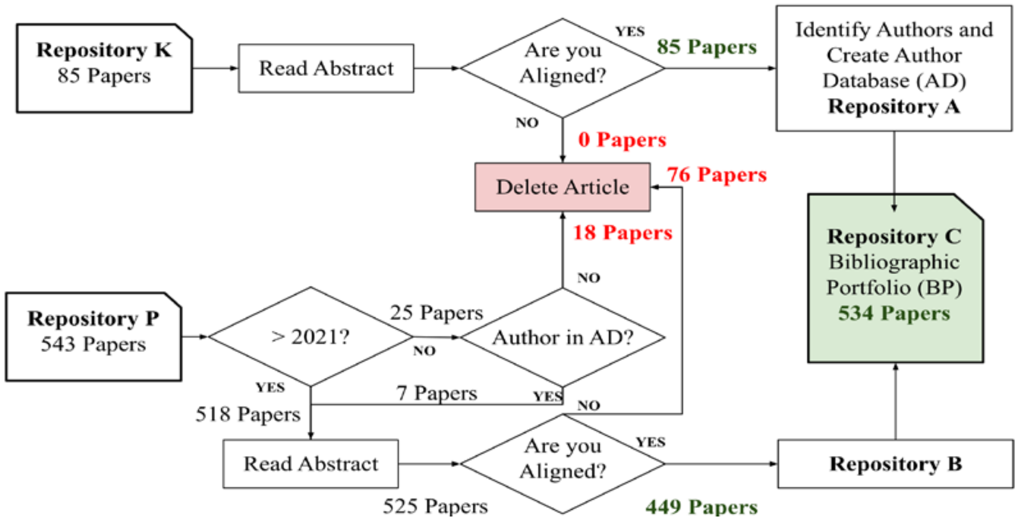


Figure 2. Flow II for obtaining the bibliographic portfolio.

K Repository Alignment: The abstracts of the papers considered as scientifically recognized are analyzed by the researcher(s) to determine whether the research aligns with the intended research objectives. If the article is aligned, it remains in the ProKnow-C flow; otherwise, it is excluded. The 85 articles in repository K were considered as aligned with SoH estimations using ML.

Creation of the Author Database (AD) and Repository A: This step involves identifying the authors of the papers approved in the previous step and creating a database of authors deemed as relevant to the research theme. The selected papers are considered as aligned with the research theme and form repository A, which constitutes the first part of the final portfolio.

P Repository Alignment: This step analyzes the papers that did not reach the level of scientific recognition. These papers are divided into two categories based on their year of publication. Articles published more than two years ago are pre-selected if one of their authors is present in the AD corresponding to repository A. If no match is found in the author database, the papers are excluded. The remaining papers are then evaluated for abstract alignment, and if the expected alignment is confirmed, they are approved in the flow and included in repository B. Recent articles are not evaluated based on the AD; instead, their abstracts are directly analyzed for alignment, and approved papers are added to repository B. In this case study, in the initial analysis of repository P, which contained a total of 543 papers, 518 were recent publications from the past two years. Of the twenty-five articles older than two years, eighteen were excluded because of the absence in the AD, and the remaining seven were added to the group containing the 518 recent papers. Of the 525 papers analyzed in this stage, 449 were found to be aligned and formed repository B.

Creation of Repository C: This step involves combining repositories A and B to form the final bibliographic portfolio resulting from the application of ProKnow-C. The final portfolio comprises papers aligned with the research theme, including scientifically recognized studies in terms of citations, recent articles with potential, and publications by researchers deemed as relevant to the field.

The union of repositories A and B forms the final bibliographic portfolio with 534 papers, representing about 9% of the initial raw paper portfolio. From this group, a high degree of alignment with the research is expected, along with the ability to describe the current state of the art, serving as a basis for the development of the target research. Table 3 presents the 40 most relevant papers in terms of the number of citations in the final portfolio. This number is based on the recommendation from [32] to evaluate an ideal volume of between 20 and 40 papers. However, each field of research and development phase has its own characteristics that influence the ideal volume of papers. Because this work aims to reveal the current research scenario within SoH estimation using ML, a portfolio approximately ten times larger than the volume recommended by [21] was constructed to enable more robust inferences regarding the algorithms employed, datasets used, and performances achieved.

Table 3. Top 40 papers from the bibliographic portfolio.

Title	Citations	Ref.
Data-driven prediction of battery cycle life before capacity degradation	1453	[1]
Long short-term memory recurrent neural network for remaining-useful-life prediction of lithium-ion batteries	880	[44]
Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review	749	[10]
A data-driven approach with uncertainty quantification for predicting future capacities and remaining useful life of lithium-ion batteries	434	[45]
Predicting the states of charge and health of batteries using data-driven machine learning	405	[46]
Random forest regression for online capacity estimation of lithium-ion batteries	398	[47]
Remaining-useful-life prediction for lithium-ion batteries based on a hybrid model combining the long short-term memory and Elman neural networks	316	[48]
Remaining-useful-life prediction for lithium-ion batteries: A deep-learning approach	313	[49]
A data-driven auto-CNN-LSTM prediction model for lithium-ion-batteries' remaining useful life	291	[50]
State-of-health estimation and remaining-useful-life prediction for the lithium-ion battery based on a variant long short-term memory neural network	284	[51]
Machine learning applied to electrified-vehicle-batteries' state-of-charge and state-of-health estimations: State of the art	267	[11]
Modified Gaussian process regression models for cyclic capacity prediction of lithium-ion batteries	262	[52]
A deep-learning method for online capacity estimation of lithium-ion batteries	260	[53]
Machine-learning pipeline for batteries' state-of-health estimations	246	[54]
A neural-network-based method for RUL prediction and SOH monitoring of lithium-ion batteries	245	[55]
A novel estimation method for the state of health of lithium-ion batteries using a prior-knowledge-based neural network and a Markov chain	239	[56]

Table 3. *Cont.*

Title	Citations	Ref.
A data-driven predictive prognostic model for lithium-ion batteries based on a deep-learning algorithm	237	[57]
Novel battery state-of-health online estimation method using multiple health indicators and an extreme-learning machine	232	[58]
Online capacity estimation of lithium-ion batteries with deep long short-term memory networks	230	[59]
A review of second-life Li-ion batteries: prospects, challenges, and issues	213	[12]
State-of-health prediction of lithium-ion batteries: Multiscale logic regression and Gaussian process regression ensemble	204	[60]
A novel deep-learning framework for the state-of-health estimation of lithium-ion batteries	203	[61]
A review of state-of-health estimations and remaining-useful-life prognostics of lithium-ion batteries	200	[13]
Synchronous estimation of state of health and remaining useful lifetime for lithium-ion batteries using the incremental capacity and artificial neural networks	195	[62]
Deep-reinforcement-learning-based energy storage arbitrage with accurate lithium-ion-battery degradation model	193	[63]
State-of-health estimation and remaining-useful-life prediction for lithium-ion batteries using a hybrid data-driven method	190	[64]
Transfer learning with a long short-term memory network for the state-of-health prediction of lithium-ion batteries	184	[65]
Battery health prediction using fusion-based feature selection and machine learning	184	[66]
A review of non-probabilistic machine-learning-based state-of-health estimation techniques for lithium-ion batteries	180	[67]
A critical review of improved deep-learning methods for the remaining-useful-life prediction of lithium-ion batteries	159	[5]
Deep Gaussian process regression for lithium-ion-batteries' health prognosis and degradation mode diagnosis	148	[68]
Model migration neural network for predicting battery-aging trajectories	147	[69]
Toward the swift prediction of the remaining useful life of lithium-ion batteries with end-to-end deep learning	144	[8]
Lithium-ion-batteries' capacity estimation—A pruned convolutional neural network approach assisted by transfer learning	142	[7]

Table 3. *Cont.*

Title	Citations	Ref.
Identification and machine-learning prediction of the knee point and knee onset in capacity degradation curves of lithium-ion cells	142	[70]
Deep-learning-based prognostic approach for lithium-ion batteries with adaptive time-series prediction and online validation	134	[71]
Predictive battery-health management with transfer learning and online model correction	122	[72]
One-shot battery-degradation-trajectory prediction with deep learning	121	[73]
Online health diagnosis of lithium-ion batteries based on a nonlinear autoregressive neural network	117	[74]
Sorting, regrouping, and echelon utilization of large-scale retired lithium batteries: A critical review	117	[9]

Among the papers listed in Table 3, we consider the work in [1] to be one of the most important in the field, a cornerstone article on the use of ML in predicting batteries' SoHs. Furthermore, it was responsible for constructing one of the first openly available datasets and widely disseminated in subsequent studies. The decision to allow research reproduction by keeping the dataset open certainly contributed to the increase in the number of publications in the field, allowing researchers to overcome limitations in result reproducibility and understanding and compare approaches. For example, several studies, [8,54,66,70,72], make use of this dataset and have a significant number of citations.

The studies conducted by [5,9–13,67] correspond to reviews, whereas [9,10,12] present more qualitative views regarding the use of ML in studying battery degradation, pointing out challenges and trends, types of algorithms that can be employed, and the potential gain that data-driven inferencing techniques can have in the characterization of second-use batteries. In [11], a more focused survey is conducted on the performance of some ML algorithms, with a comparison between different neural network structures, including DL architectures. Similarly, in [5], the authors also perform an analysis of DL algorithms, a topic which is also present in [67], along with other non-probabilistic methods. In [13], approaches are presented, along with comparisons of algorithms and their performances in predicting SoH response variables.

The presence of public datasets is evident in 15 out of the 33 non-review papers from Table 3, namely, studies [1,8,49–51,54,55,57,60,61,64,66,68,70,72], which utilize data from institutions such as the Prognostics Data Repository (NASA), the Center for Advanced Life Cycle Engineering (CALCE, the University of Maryland), the Massachusetts Institute of Technology (MIT, which constructed the dataset in [1]), and the University of Oxford. Further details about the datasets and techniques will be discussed later, considering analyses of the entire portfolio obtained.

2.2. Bibliometric Analysis of the Bibliographic Portfolio

After defining the bibliographic portfolio, the bibliometric analysis stage seeks a quantitative analysis of the information present in the publications and their characteristics [36]. In this paper, five aspects presented in [35] were considered: (i) scientific recognition of the papers; (ii) recognition of the authors; (iii) recognition of the journals; (iv) most used keywords; (v) bibliographic reviews.

2.2.1. Scientific Recognition of the Papers

The first analysis concerns the publication history within the 534 papers of the final bibliographic portfolio, which is shown in the graph in Figure 3, in terms of annual volume and cumulative frequency. It is noted that approximately 45% of the portfolio corresponds to publications from 2023 (and the first two weeks of 2024), indicating the ongoing relevance of the addressed topic and instigation for discoveries in the research field as a trend. This trend highlights the rapid expansion of research in battery SoH estimation, driven by advancements in artificial intelligence (AI) and the growing demand for sustainable energy storage solutions. The alignment of research topics among authors in recent years reflects the global focus on the reuse of lithium-ion batteries and their role in mitigating environmental impacts associated with electric-vehicle-battery waste [12].

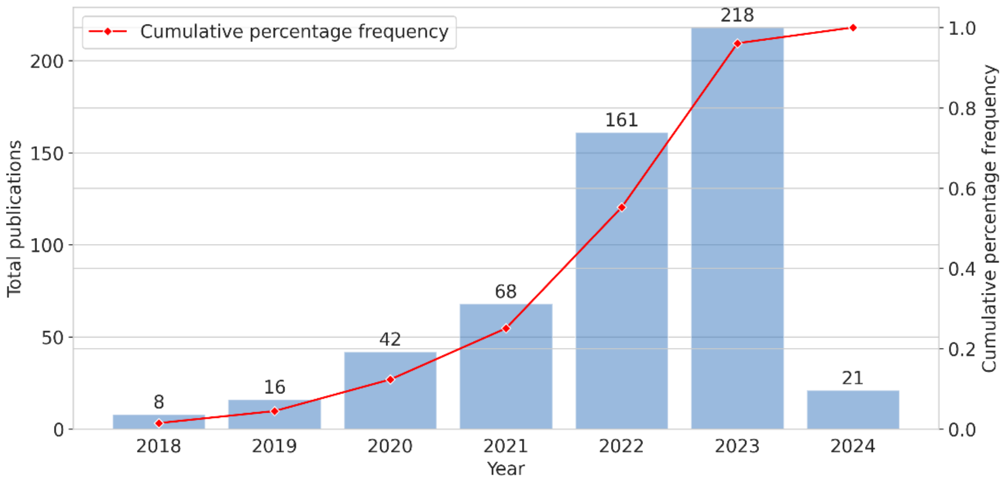


Figure 3. Volumetric analysis of the year of publication in the bibliographic portfolio.

The selected papers from the first week of 2024 already represent a higher volume than the publications from 2018 and 2019, indicating that the alignment of research topics among authors is more recent. Overall, we can observe a trend of research growth in the area when analyzing the growth curve within the obtained portfolio. This is further supported by the intensification of the automobile electrification process, which requires robust methodologies to ensure effective battery health monitoring and reuse [75–77].

Another analysis performed corresponds to the scientific relevance of the papers in the portfolio according to the year of publication, as presented in Figure 4. It is possible to identify the top three most cited papers in the portfolio, published in 2018 and 2019. These cornerstone studies, focused on the use of ML techniques for SoH estimation, have laid the foundation for subsequent studies and have significantly influenced citation patterns. The increasing density of publications over the years, coupled with a reduction in citation intervals, indicates an accelerated dissemination and application of SoH methodologies.

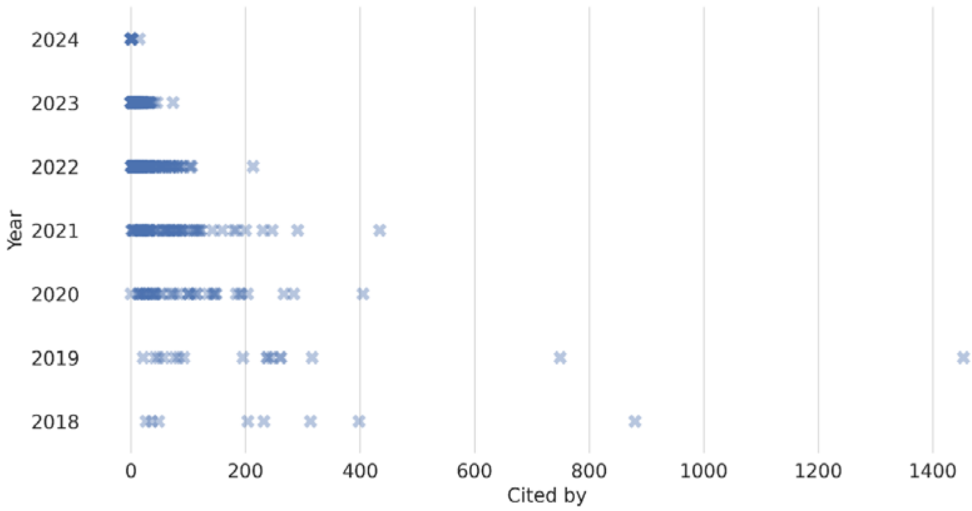


Figure 4. Analysis of the number of citations per year of publication in the bibliographic portfolio.

2.2.2. Author Recognition

The bibliographic portfolio consists of 2593 authors, of which 1967 are unique. The analysis of the distribution of the number of authors per article, presented in Figure 5, indicates that on average and in the median, the articles have five authors, with 30% of the publications having six or more authors, and 98% of the publications having up to ten authors. This median aligns with common collaborative efforts in technical and scientific research, particularly in interdisciplinary fields, such as ML and battery SoH estimation, where diverse expertise is critical.

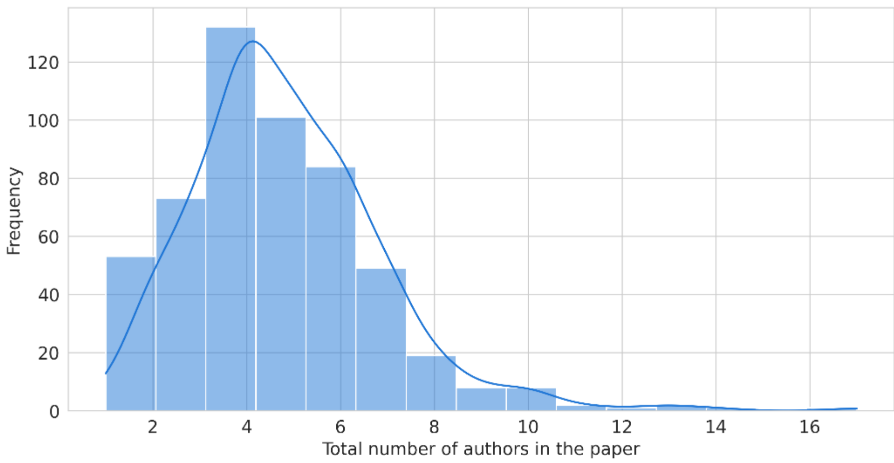


Figure 5. Analysis of the number of authors per publication in the bibliographic portfolio.

The graph in Figure 6 presents the number of papers in which an author is involved. For example, we notice that only one author is present in nine articles in the BP, while 1586 authors are present in only a single article in the BP. Approximately 80% of the authors are present in only one publication, while only 10% of the authors are present in two or more publications. This distribution highlights a high dispersion degree of knowledge within the portfolio, indicative of a field still expanding and attracting a broad range of contributors. Although this diversity enriches the field, it also emphasizes the need for more concentrated and sustained collaborations among leading authors to build upon foundational research.

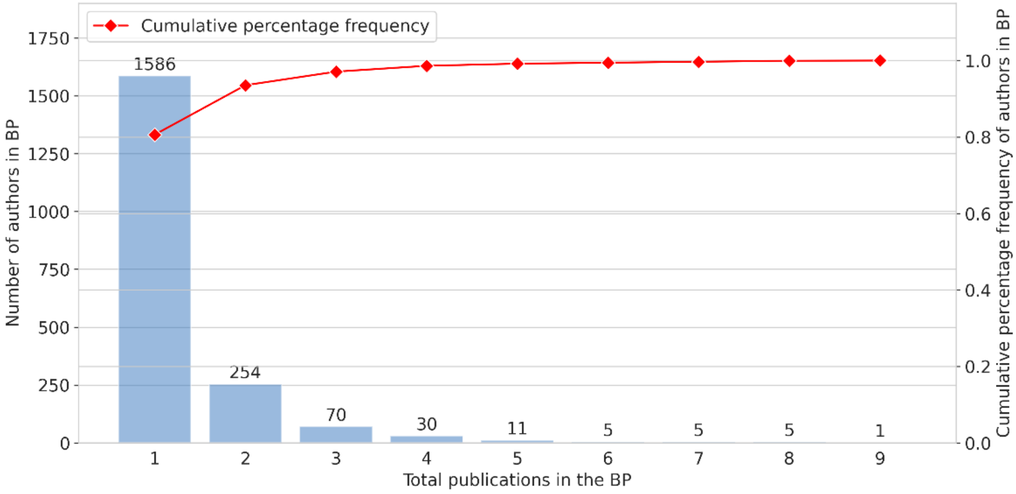


Figure 6. Analysis of the number of publications per author in the bibliographic portfolio.

Figures 7 and 8 provide additional insight. Figure 7 shows the top 30 most prolific authors in the portfolio, offering a reference for identifying influential researchers in the field. Figure 8 illustrates the connections between authors, revealing networks of collaboration. These interconnected clusters suggest that some authors are central to advancing SoH estimation using ML, potentially forming hubs of expertise within this research area.

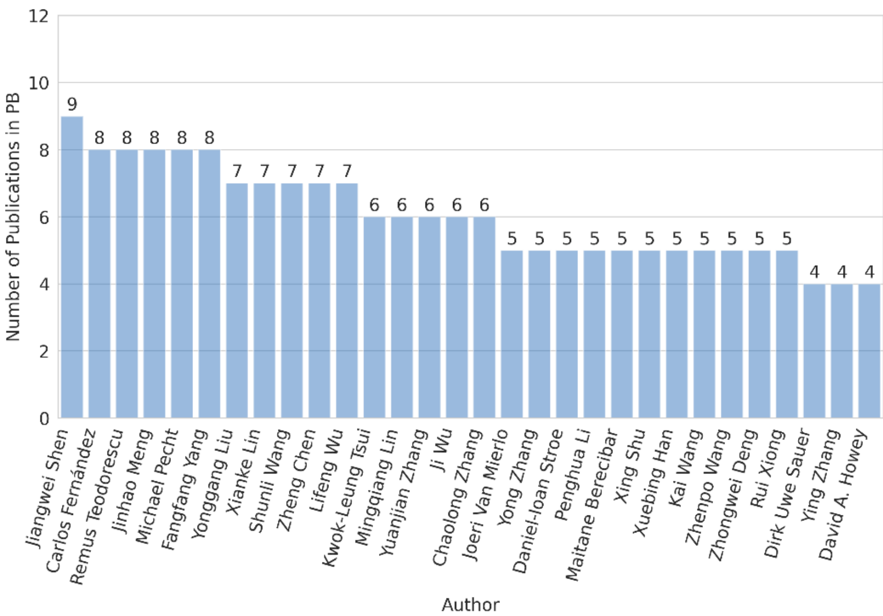


Figure 7. Top 30 authors with the highest participation in the bibliographic portfolio.

Figures 5–8 together underline the importance of collaboration networks and prolific authors in driving innovation. Mapping these connections offers a valuable tool for researchers aiming to identify trends, access seminal studies, or join active research groups in batteries' SoHs and ML.

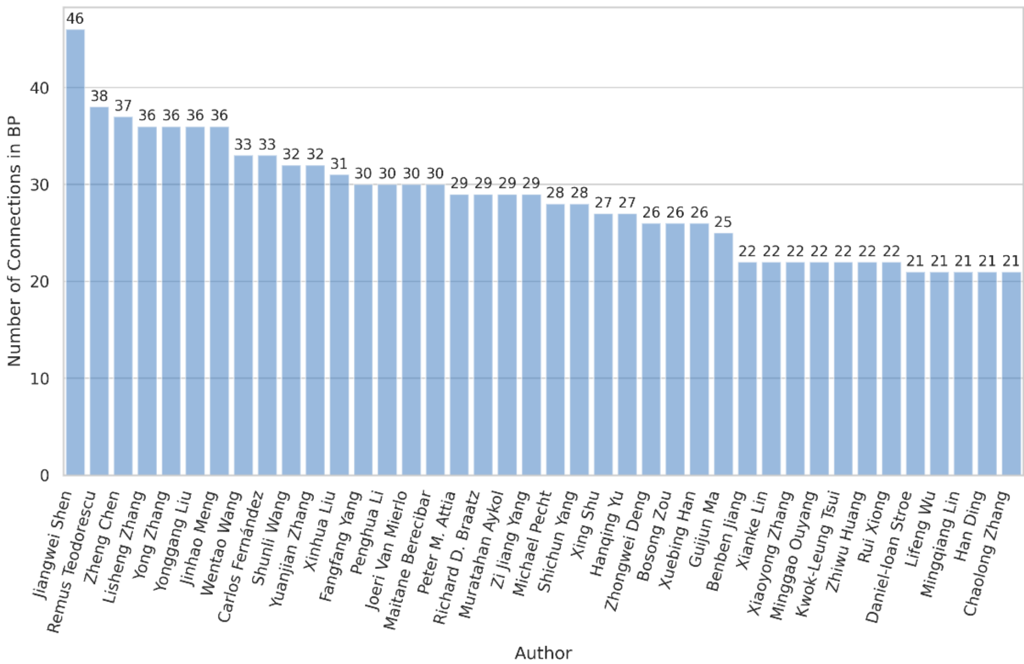


Figure 8. Authors with the most connections within the bibliographic portfolio.

2.2.3. Relevance of Journals

The distribution of journals, as presented in Figure 9, highlights the diversity of publication venues. Journals with one publication in the portfolio were grouped into the "Others" category. About 13% of the portfolio is present in these journals, indicating the variety of journals covering the topic. The category "Others" comprises 72 journals. The *Journal of Energy Storage* is the most represented, accounting for 15% of the total number of publications in the portfolio, emphasizing its central role in disseminating research on batteries' SoHs.

Approximately 55% of the papers in the final portfolio are open access, reflecting the increasing emphasis on making research accessible to a broader audience. Among them is the journal *Energies*. The diversity of journals within this portfolio also reflects a range of main subjects, including sustainable and renewable energies, information technology and computing, system control and automation, computer science and engineering, electrical and electronic engineering, and, primarily, artificial intelligence and ML. This demonstrates how the SoH estimation of batteries is a broad research field and that researchers from different areas are seeking solutions through artificial intelligence.

Figure 9 highlights the growing centralization of SoH research in a few key journals, indicating a maturing field. This concentration not only facilitates a more focused dissemination of cutting-edge research but also provides a reliable reference for scholars and practitioners aiming to access the most impactful findings in the area.

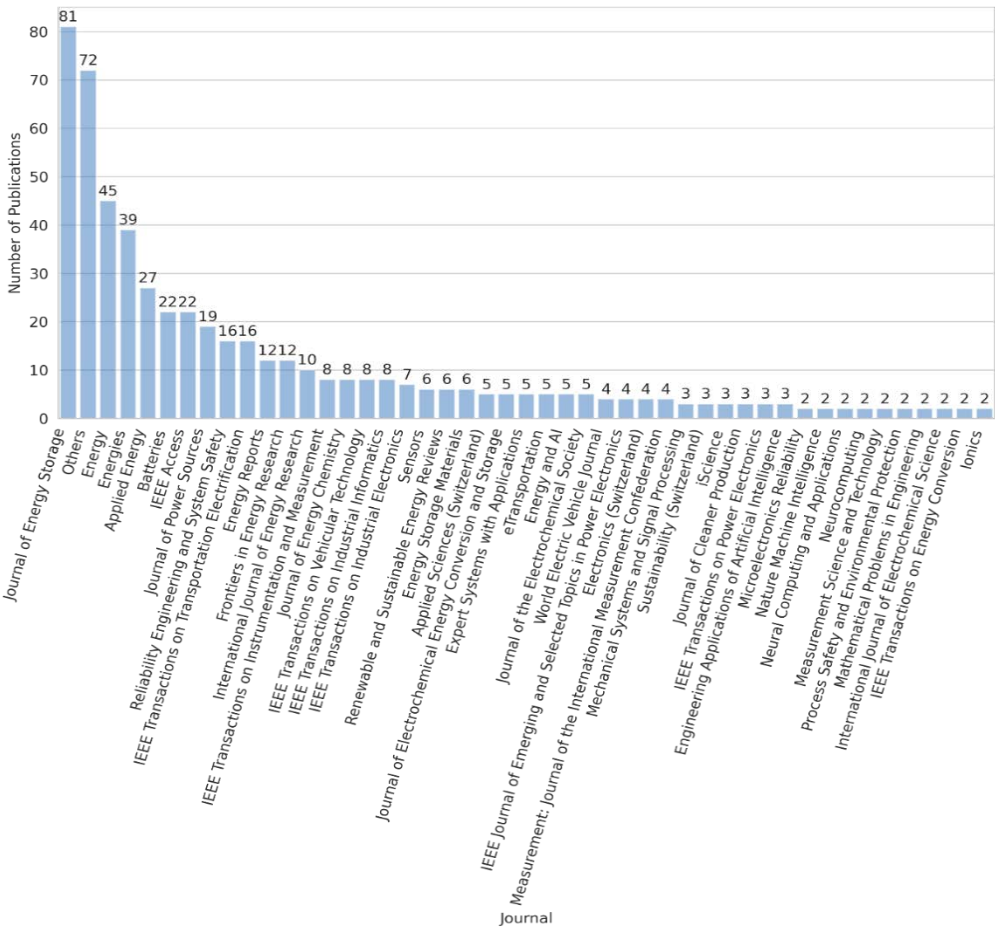


Figure 9. Distribution of the number of publications by journal in the bibliographic portfolio.

2.2.4. Relevance of Keywords

The bibliographic portfolio consists of 2753 keywords, of which 1044 are unique. Figure 10 presents the distribution of the keywords, where a significant concentration is observed for the terms “lithium-ion battery” and “state of health”, which are, indeed, the objects and central themes of this research. The prominence of “state of health” reinforces its position as a pivotal concept in this study, guiding much of the research efforts in this field. Additionally, “machine learning” appears as the fifth most frequent term, reflecting the critical role of artificial intelligence in advancing battery SoH estimation.

The term “remaining useful life” is also notable, corresponding to one of the main response variables in the study of the SoH. Regarding techniques, the frequent appearances of “LSTM neural networks” and “deep learning” highlight the increasing adoption of advanced computational models. This reflects the growing sophistication in predictive analytics, as researchers seek more accurate and robust approaches to model battery degradation.

Figure 11 depicts the distribution of keyword connections within the selected papers. The pattern of terms mirrors the previous distribution, showing how central keywords, such as “state of health” and “machine learning”, branch out across diverse contexts. This interconnectedness illustrates the multidisciplinary nature of SoH research, bridging fields like energy systems, artificial intelligence, and sustainability.

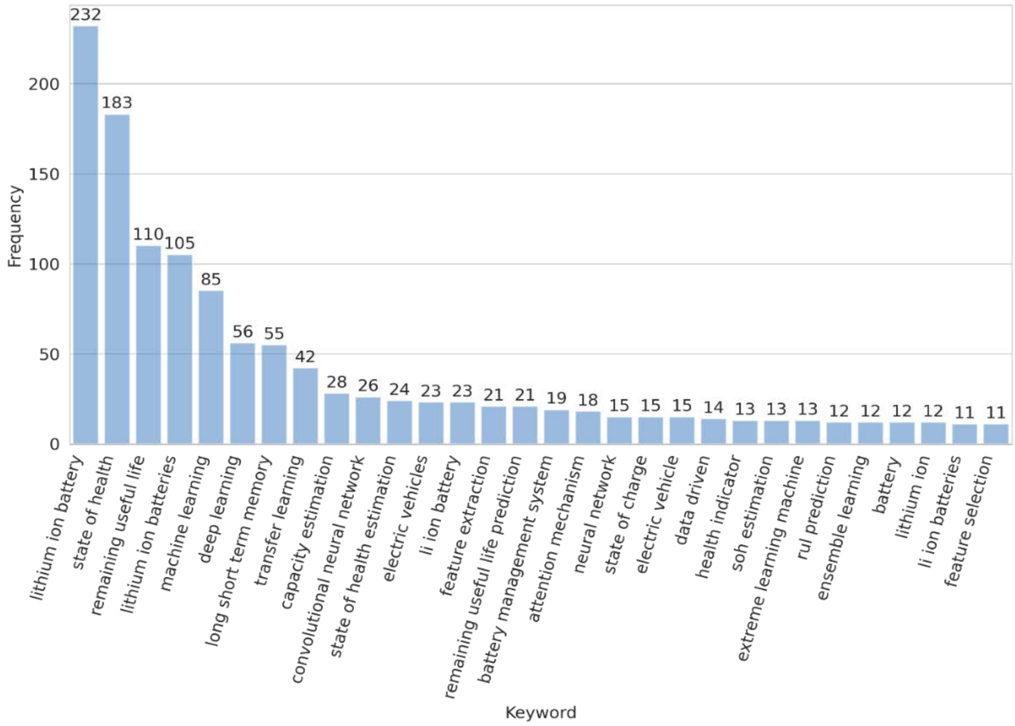


Figure 10. Distribution of keywords in the bibliographic portfolio.

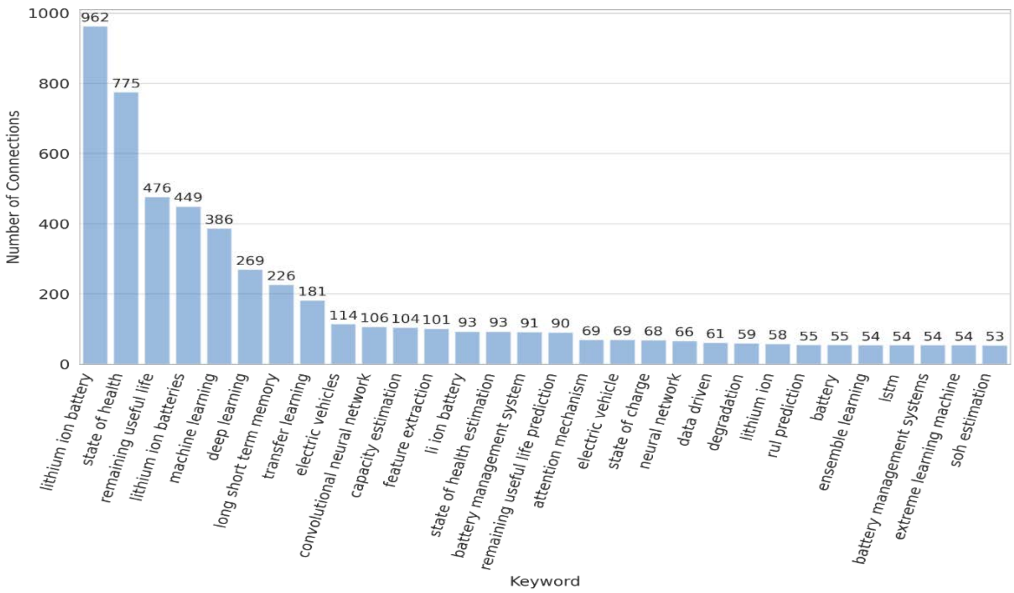


Figure 11. Number of connections of keywords within the bibliographic portfolio.

Figures 10 and 11 together emphasize the importance of keywords in structuring and advancing the field. Although the dominant terms reflect the current research focus, the variety and connections among keywords indicate the evolving boundaries of the field and its responsiveness to emerging challenges and technologies.

3. Content Analysis

The bibliographic portfolio of 534 papers, following the ProKnow-C methodology analyzed in the previous section, was explored to characterize the current scenario in the field of SoH estimation in batteries. First, we outline the survey of public databases found in the bibliographic portfolio, followed by the techniques and algorithms implemented in the papers. The algorithms are further analyzed according to categories of modeling, including DL, algorithmic hybridization, and transfer learning. A situational overview of the performance is highlighted, and key review studies in the field are analyzed. This section concludes with implications for energy informatics and intelligent systems.

3.1. Portfolio Overview

Except for review papers, the objectives of the studies are directly related to establishing various forms, either algorithmically or through different approaches, to perform SoH estimation. In the presentation of the most cited papers in Table 3, it is noted that there is a significant focus on testing different types of ML algorithms and how their methods can increase the accuracy of SoH estimation. This is the case with the study presented in [44] with long short-term memory (LSTM) neural networks, the combination of LSTM and extreme-learning-machine (ELM) neural networks presented in [48], or the use of ensemble methods, such as bagging in decision trees, through the random forest (RF) algorithm in [47]. In summary, papers with the highest number of citations in the portfolio typically focus on increasing estimation accuracy through experiments related to algorithms.

Compatible studies can also be highlighted, such as the study presented in [78], which compares the LSTM, FNN, and CNN neural network algorithms, where the LSTM algorithm achieved the best performance, with an MAPE (mean absolute percentage error) of around 0.5%, compared to about 1.5% for FNN and 2% for CNN networks. In [79], the authors compare different probabilistic and time-series algorithms (ARIMAX, linear quantile regression, bootstrap multiple linear regression, and Bayesian bootstrap multiple linear regression), with the best results obtained from the Bayesian bootstrap multiple linear regression algorithm's quantile regression, which achieved MAPE values ranging from 0.2% to 1%. Other highlighted comparative studies include [66,80].

The concept of feature engineering, which includes manipulation and selection, is a relevant theme presented in the portfolio, as much of the algorithm's performance lies in the stress of creating features that provide discrimination for predictions. Study [81] introduces an autonomous feature selection method, which is based first on an initial selection considering correlation coefficients, tree algorithms, and a variance factor, followed by an iterative method for feature combination. In [82], an analysis of feature engineering for SoH estimation is presented, evaluating different techniques for feature creation and selection, such as univariate selection by Pearson correlation, feature importance, feature clustering, genetic algorithms, and sequential feature selection. The authors concluded that the use of sequential selection presented a good balance between performance and computational cost. Feature tests were evaluated using SVM and ExtraTree-based algorithms. Other studies focusing on features can be consulted in [81,83–96].

The quest for automating modeling processes was found in the development of an autoML approach in [97]. The framework built is capable of performing the entire modeling cycle using Bayesian optimization, eliminating the need for researchers from other fields to spend time on laborious steps, such as feature extraction, construction, and selection. The results obtained yielded MAEs (median absolute errors) ranging from about 0.02% to 0.05% for SoH estimation.

Interpretability model analyses were found in studies [98,99], based on the use of a technique known as SHAP (Shapley Additive Explanations). SHAP is based on a theoretical game approach that seeks to explain the output of any ML model by quantifying how each feature impacts the model's prediction [100,101]. Other model interpretability approaches were also addressed in [102–105].

Approaches related to hyperparameter tuning were also found in the portfolio. In [106], the authors explore the Bayesian optimization of hyperparameters in a combination of DCNN and LSTM neural networks, achieving an RMSE (root-mean-square error) of 0.0061 for SoH estimation. In study [107], a pipeline optimization based on a tree and genetic algorithm is presented. Study [108] also uses a genetic algorithm as a means of parameter optimization, presenting a framework for SoH estimation, with errors of about 2%.

The use of sensors for capturing battery conditions implies tabular data; however, studies were found in the portfolio, which analyze the implementation of image-based algorithms for SoH prediction. In [109], the authors propose a method capable of using only one charge and discharge cycle for SoH prediction, using image processing of current and voltage curves. Using transfer learning, the authors achieved an MAPE in the range of 10%. Transfer learning is also used in the algorithm based on battery curve image analysis in [110]. The authors analyze images of one cycle, five cycles, and ten cycles, with MAEs of about fifty, fifty-five, and sixty cycles, respectively, using eight pretrained networks, such as ResNet and GoogleNet. Other studies using algorithms from the computer vision area were found in [111–113].

Regarding the cell technologies employed, almost all the publications correspond to lithium-ion technology, among which we can highlight LFP (lithium iron phosphate), LCO (lithium cobalt oxide), NCA (lithium nickel cobalt aluminum oxide), and NMC (lithium nickel manganese cobalt oxide) battery types. Only three studies made use of battery technologies different from lithium. Study [114] analyzes the estimation of the SoHs of removed lead–acid batteries, aiming for reuse. In [115], lead–acid batteries are also analyzed, and the authors develop an SoH prediction model using LSTM networks based on charge curve data. In [116], the authors use a neural network to predict the remaining lifespan of a zinc-ion battery.

3.2. Literature Review

Within the article selection process, 38 papers correspond to review papers, and they are presented in Table 4. The papers are essentially divided into reviews with qualitative analyses (e.g., trends, challenges, and general overviews), as well as papers more focused on a specific set of techniques and surveying performances and the extraction of degradation features and health indicators. In all the analyzed papers, there was no indication of the use of a methodological process for selecting the bibliographic portfolio, highlighting the importance of this work as a point of evolution within the research field.

Table 4. Review papers in the bibliographic portfolio.

Title	Year	Cited	Ref.
Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review	2019	749	[10]
Machine learning applied to electrified-vehicle-batteries’ state-of-charge and state-of-health estimation: State of the art	2020	267	[11]
A review of second-life Li-ion batteries: prospects, challenges, and issues	2022	213	[12]
A review of state-of-health estimations and remaining-useful-life prognostics of lithium-ion batteries	2021	200	[13]
A review of non-probabilistic machine-learning-based state-of-health estimation techniques for lithium-ion batteries	2021	180	[67]

Table 4. *Cont.*

Title	Year	Cited	Ref.
A critical review of improved deep-learning methods for the remaining-useful-life prediction of lithium-ion batteries	2021	159	[5]
Sorting, regrouping, and echelon utilization of large-scale retired lithium batteries: A critical review	2021	117	[9]
Big training data for artificial-intelligence-based Li-ion diagnoses and prognoses	2020	100	[117]
Machine learning in state-of-health and remaining-useful-life estimation: Theoretical and technological developments in battery degradation modeling	2022	88	[118]
State-of-health prediction of lithium-ion batteries based on machine learning: Advances and perspectives	2021	81	[119]
A critical review of improved deep convolutional neural networks for multi-timescale state prediction of lithium-ion batteries	2022	75	[30]
A review of deep-learning approaches to predict the states of health and states of charge of lithium-ion batteries	2022	69	[26]
A critical review of online battery-remaining-useful-lifetime prediction methods	2021	62	[120]
Artificial neural networks, gradient boosting, and support vector machines for electric-vehicle-batteries' state estimation: A review	2022	57	[31]
State-of-health estimation and remaining-useful-life assessment of lithium-ion batteries: A comparative study	2022	43	[121]
A review of modern machine-learning techniques in the prediction of the remaining useful life of lithium-ion batteries	2023	34	[122]
Overview of machine-learning methods for lithium-ion-batteries' remaining-useful-lifetime prediction	2021	33	[123]
A review of machine-learning-based state-of-charge and state-of-health estimation algorithms for lithium-ion batteries	2023	33	[124]
Transfer learning for batteries' smarter-state estimation and aging prognostics: Recent progress, challenges, and prospects	2023	32	[27]
Review of "gray box" lifetime modeling for lithium-ion batteries: Combining physics and data-driven methods	2022	31	[125]

Table 4. *Cont.*

Title	Year	Cited	Ref.
Deep-learning-enabled state-of-charge, state-of-health, and remaining-useful-life estimations for smart battery management systems: Methods, implementations, issues, and prospects	2022	26	[24]
Explainability-driven model improvement for SOH estimation of lithium-ion batteries	2023	20	[126]
State estimation models of lithium-ion batteries for battery management systems: Status, challenges, and future trends	2023	20	[127]
State-of-charge, remaining-useful-life, and knee-point estimations based on artificial intelligence and machine learning for lithium-ion EV batteries: A comprehensive review	2022	19	[128]
The development of machine-learning-based remaining-useful-life predictions for lithium-ion batteries	2023	17	[129]
Comprehensive review of battery state estimation strategies using machine learning for battery management systems of aircraft propulsion batteries	2023	16	[130]
A comprehensive review of lithium-ion-batteries' state-of-health prognosis methods combining aging mechanism analysis	2023	11	[131]
Research progress and application of deep learning in remaining-useful-life, state-of-health, and battery thermal management of lithium batteries	2023	11	[132]
A review of the prediction of the health state and serving life of lithium-ion batteries	2022	7	[6]
Specialized deep neural networks for battery health prognostics: Opportunities and challenges	2023	7	[25]
Machine-learning techniques' suitability to estimate the retained capacity in lithium-ion batteries from partial charge/discharge curves	2023	7	[133]
Deep feature extraction in lifetime prognostics of lithium-ion batteries: Advances, challenges, and perspectives	2023	6	[28]
Comparing deep-learning methods to predict the remaining useful life of lithium-ion batteries	2022	4	[134]
Machine-learning-based remaining-useful-life prediction techniques for lithium-ion-battery management systems: A comprehensive review	2023	2	[29]
Feature–target pairing in machine learning for battery health diagnosis and prognosis: A critical review	2023	2	[135]

Table 4. *Cont.*

Title	Year	Cited	Ref.
Research on methods for extracting aging characteristics and the health status of lithium-ion batteries based on small samples	2022	1	[136]
Electric-vehicle-batteries' capacity degradation and health estimation using machine-learning techniques: A review	2023	0	[137]
Open access dataset, code library, and benchmarking deep-learning approaches for state-of-health estimations of lithium-ion batteries	2024	0	[138]

Figure 12 shows that the number of review article publications within the portfolio has been increasing over the years, albeit with a considerably lower coefficient compared to that of the overall volumetric analysis. There appears to be a difference between 2022 and 2023, suggesting a potential trend toward stability in the coming years.

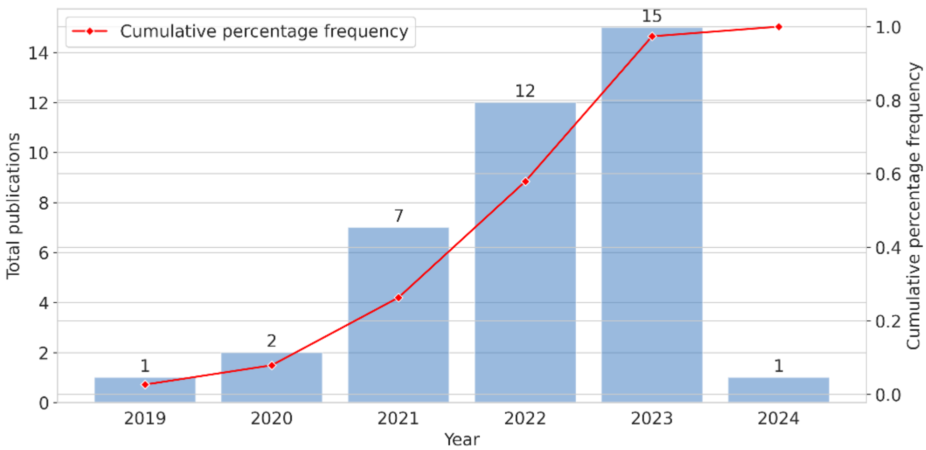


Figure 12. Volumetric analysis of the publication year of review papers in the BP.

The most cited review article in the portfolio is the study presented in [10], which examines big-data techniques regarding their feasibility and cost effectiveness in dealing with battery health in real-world applications. The methods are categorized, and advantages and limitations are identified. The authors begin by presenting methods that do not involve model training, such as the differential analysis of charge and discharge profiles, stress tests, and thermal analyses. Then, they review the use of ML for SoH estimation, highlighting the fundamental step of feature extraction. They categorize these features into three main groups: (i) model-fitted features, which depend on tests like internal resistance and are not easily accessible by sensors in a BMS (battery management system); (ii) processed external features, which are the results of differential analyses; and (iii) direct external features, which are all the variables that a sensor can collect within the battery system and can generate a large number of variables. The authors also briefly review non-probabilistic ML methods, such as artificial neural networks, SVMs, and probabilistic models, like Gaussian regression.

The non-probabilistic methods are the central theme of the study presented in [67], where five types of ML algorithms for batteries' SoH estimation are reviewed: linear regression, SVM, KNN, neural networks, and ensemble methods. The study comparatively outlines the advantages and applicability of the different methods from a theoretical standpoint. Three aspects are considered for comparing the methods: the algorithm's performance based on five performance metrics (RMSE, MAE, AE, APE, and MaxE), the publication trend obtained by counting the number of publications in the last ten years, and the training modes considering feature extraction and selection. The study used 144 papers considered as relevant and published up to 10 years before (with the reference year being 2021), however, without revealing the criteria used for obtaining the portfolio. The authors conclude that neural-network-based methods and SVMs are still under research and that DL methods have shown great potential in SoH estimation under complex battery-aging conditions, especially when big data are available, and that ensemble methods, like random forest, can be considered as an emerging alternative for balancing data size and accuracy.

Regarding the use of ML techniques in second-life batteries, the study presented in [9] reviewed the status and challenges of large-scale second-life applications. The authors discuss methodologies for classifying and regrouping retired batteries. They propose a rapid, multilevel, and multidimensional classification method for large-scale use. The classification method involves first solving a one-dimensional classification problem to obtain similar batteries in terms of their reaction stage. Then, a multidimensional classification is performed based on capacity and internal resistance, where usage scenarios are evaluated, for example, to determine whether the priority use is for energy or power supply. The second life is also discussed in the review presented in [12], which analyzes economic, technical, and environmental factors related to the use of second-life lithium-ion batteries, including SoH estimation methods.

Regarding the reviews from this year, it is worth highlighting the study in [27], which presents the first systematic review of transfer-learning applications in the field of battery management, focusing on batteries' state estimations and aging prognoses. The authors provide the state of the art in terms of principles, algorithmic structures, advantages, and disadvantages. For SoH estimation, a survey of papers in the field showed that transfer strategies focus on problem domain adaptation and the fine-tuning of the final model. The difficulties pointed out by the authors in using transfer learning lie in the low labeling degree of the data, which depends on the data acquisition capability at shorter intervals in a BMS. This is exacerbated by the low frequency of actual battery capacity testing during usage, especially for SoH estimation purposes.

3.3. Public Databases

Analyzing the non-review papers present in the bibliographic portfolio, it was found that about 41% make use of proprietary and closed datasets, without sharing repositories for use in other studies. On the other hand, a significant and increasingly growing portion of papers conduct investigations using public datasets, comprising 59% of the non-review papers in the portfolio. As emphasized in [11], advancements in the field of ML for estimating batteries' SoHs rely on information sharing so that new research can develop and result comparisons can occur, thereby allowing inferences about techniques that may enhance estimation accuracy. This scenario demonstrates this sharing trend, leading to faster and more voluminous developments in the research field. It is worth noting that fair comparative analyses of models/approaches also require the sharing of data splits used for training and testing/validation; only then can comparisons be made when dealing with the same population.

Figure 13 demonstrates that author-provided datasets have the highest frequency of use. However, the majority of these datasets are complementary to public datasets. Among these, the highlight goes to the use of data provided by the Prognostics Center of Excellence Dataset Repository [139], from NASA, which accounts for 51% of the open datasets used in the surveyed portfolio. The dataset presented in [1], developed at the

Massachusetts Institute of Technology (MIT), also constitutes an important data source in the surveyed papers.

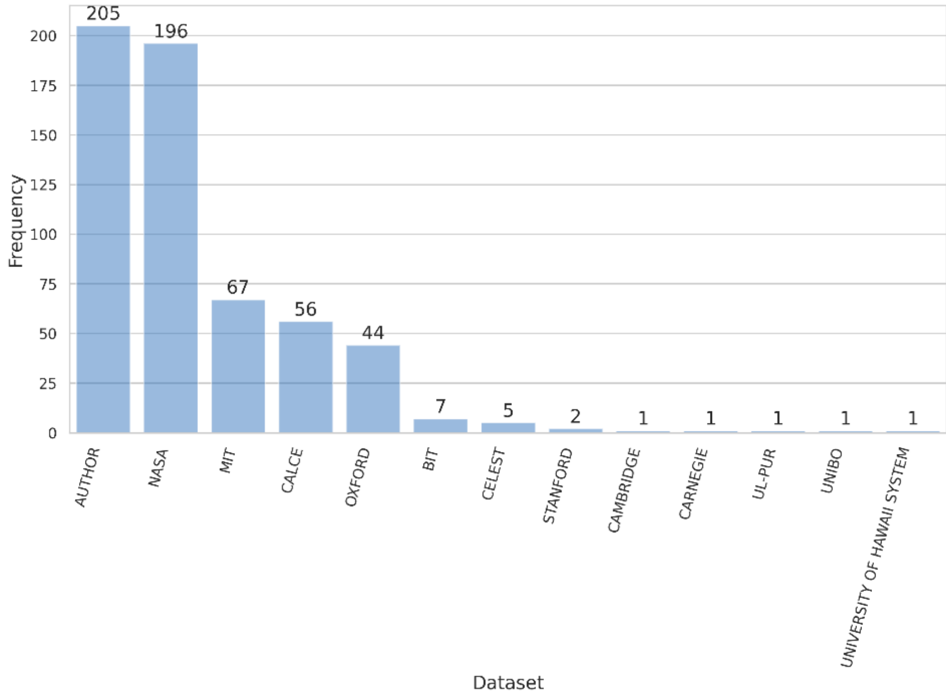


Figure 13. Volumetric analysis of datasets used in the papers of the bibliographic portfolio.

The evolution of the proportion of closed and public datasets is presented in Figure 14. It is noticeable that the volume of applications using public datasets starts to become predominant from 2022, with the use of public datasets being about 3.2 times higher in 2023. This increase could be because of the research trend of using multiple datasets, and because more data sources are available, the application of public datasets would tend to increase. Therefore, to mitigate this effect, Figure 14 considers only the Boolean condition of whether a public dataset was used or not, and the results are similar, with the number of papers using public datasets in 2023 being about 2.3 times higher than those using closed datasets.

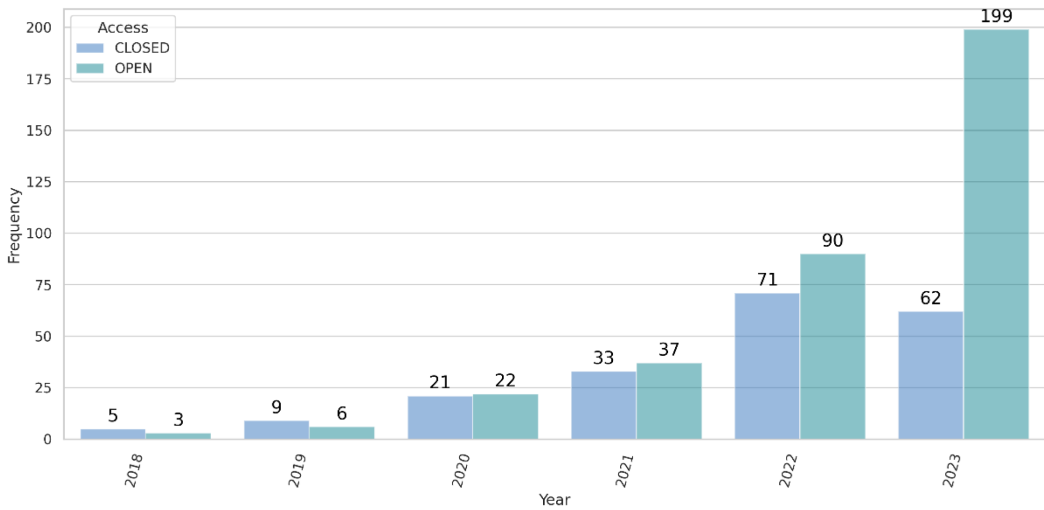


Figure 14. Annual evolution in the BP of papers using public datasets versus closed datasets.

Through an evaluation according to the dataset origin, Figure 15 illustrates the evolution of the dataset usage over the years in the bibliographic portfolio (BP). The increasing use of NASA datasets is noticeable, followed by the usage of the MIT [1], Oxford, and CALCE datasets. Other public datasets with even lower levels of usage are also identified in the portfolio: the Beijing Institute of Technology (BIT), Carnegie Mellon University, Stanford University, Cambridge University, the University of Hawaii, Purdue University (UL-PUR), the University of Bologna (UNIBO), and the Center for Electrochemical Energy Storage Ulm–Karlsruhe (CELEST).

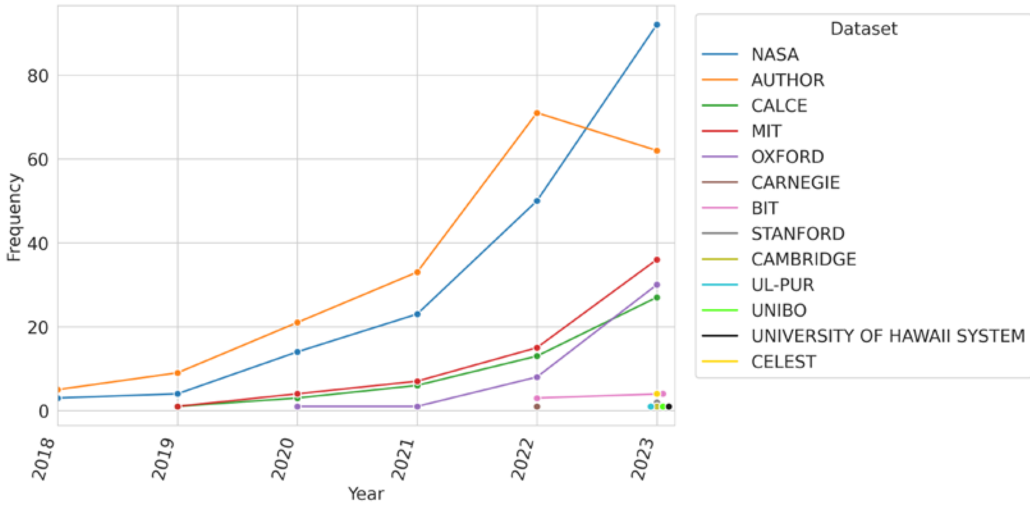


Figure 15. Annual evolution, in the BP, of the origin of public and author datasets.

Table 5 provides a summary of each of the public datasets found in the portfolio, as well as their characteristics and in which papers they were used. In total, 12 sources of public data were revealed, corresponding to 20 different datasets, all using lithium technology as the main source of the analyzed batteries. The synthesis of these databases constitutes important information for future studies, as it facilitates the selection and design of new studies on SoHs.

In the NASA repository, two datasets are available for developing models aimed at estimating SoHs. The first dataset contains 34 lithium-ion 18,650 cells with a capacity of 2 Ah, undergoing processes of charging, discharging, and impedance measurements. Various temperatures are used, including 4 °C, 24 °C, and 44 °C, with the charging process consisting of constant current until 4.2 V, followed by constant voltage until reaching the cutoff current. Different discharge regimes are adopted. The second dataset corresponds to 28 lithium-ion 18,650 cells with a capacity of 2.2 Ah that are continuously cycled with randomly generated current profiles. Reference charge and discharge cycles are also performed after a random fixed interval. In total, the cells are divided into seven equal groups, with the cycles occurring at a temperature of 40 °C. In five groups, the charging cycle follows the traditional constant current–constant voltage (CC-CV) pattern, followed by randomly selected discharges. In two groups, both the charging and discharging processes are selected randomly. The cycling processes of the cells are terminated when their capacity reached either 80% or 50% of the initial capacity, depending on the type of test defined. Both NASA datasets are provided in ".mat" extension files.

Table 5. Datasets included in the bibliographic portfolio.

Dataset	Cell Type	Features	No. of Cells	Refs.	Link
NASA	Li-ion 18650	V, I, T, IR, time	34	[49–51,54,55,57,60,61,64,66,68,78–81,87,91,96,97,106,107,140–314]	https://www.nasa.gov/intelligent-systems-division/discovery-and-systems-health/pcoe/pcoe-data-set-repository/
	Li-ion 18650	V, I, T, time	28		
MIT	$LiFePO_4$/graphite	V, I, T, IR, time	124	[1,8,54,66,70,72,83,92,94,99,102,104,110,111,140,144,199,205,253,269,277,299,315–359]	https://data.matr.io/1/projects/5c48dd2bc625d700019f3204
CALCE	$LiCoO_2$	V, I, T, time	15	[54,64,66,150,157,159,161,162,170,172–175,180,182,187,192–195,200,206,208,209,215,217,220,222,228,229,231,236,240,244,249,263,264,269,270,282,288,312,328,330,344,347,360–369]	https://calce.umd.edu/battery-data
	$LiCoO_2$	V, I, T, IR, time	12		
	$LiCoO_2$	V, I, time	16		
OXFORD	Li-ion 18650	V, I, T, time	8	[54,88,92,99,140,142,152,156,157,179,180,194,201,209,225,235,263,269,277–279,281,293,295,311,313,330,348,354,369–383]	https://ora.ox.ac.uk/objects/uuid:03ba4b01-cfed-46d3-9b1a-7d4a7bdf6fac
	Li-ion 18650	V, I, T, time	6		https://ora.ox.ac.uk/objects/uuid:9aae61af-2949-49f1-8ad5-6aea448979e5
	Li-ion 18650	V, I, T, IR, time	12		https://ora.ox.ac.uk/objects/uuid:de62b5d2-6154-426d-bcbb-30253ddb7d1e
BIT	LFP/graphite	V, I, T, time	77	[325,335,384–388]	https://data.mendeley.com/datasets/kw34hhw7xg/2
STANFORD	NMC (INR21700M50T)	V, I, T, IR, time	10	[165,389]	https://osf.io/qsabn/?view_only=2a03b6c78ef14922a3e244f3d549de78
CELEST	NCA	V, I, T, IR, time	66	[369,389–392]	https://zenodo.org/records/6405084
	NMC	V, I, T, IR, time	55		
	NCA + NMC	V, I, T, IR, time	9		
UL-PUR	NCA	V, I, T, IR, time	35	[194]	https://www.batteryarchive.org/index.html
UNIBO	Li-ion 18650	V, I, T, IR, time	27	[212]	https://data.mendeley.com/datasets/n6xg5fzsbv/1
CAMBRIDGE	LCO/graphite	V, I, T, IR, time	12	[393]	https://zenodo.org/records/3633835
University of Hawaii System	LFP/graphite	V, I, T, time	6	[394]	https://data.mendeley.com/datasets/y8nstxmdrg/1
	NMC	V, I, T, time	6		
CARNEGIE	Li-ion 18650	V, I, T, time	30	[395]	https://kilthub.cmu.edu/articles/dataset/eVTOL_Battery_Dataset/14226830/1

The dataset developed in [1] consists of 124 LiFePO4/graphite cells with a capacity of 1.1 Ah and a nominal voltage of 3.3 V. The cells were cycled at a temperature of 30 °C, being charged with a fast-charging policy of one or two steps, in the C1(Q1)–C2 format. Here, C1 and C2 represent the first and second constant current steps, respectively, and Q1 is the state of the charge (SoC, %) at which the currents change. The second current step terminates at 80% of the SoC, after which the cells charge at 1C CC-CV. The charging step can occur in a range of 72 different protocol profiles, with the discharge maintaining the same pattern across all the cycles. The cycles are terminated when the cell's capacity reaches 80% of its initial capacity. All the data are provided in ".mat" format.

The Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland provides three datasets of LiCoO2 batteries, including two sets of prismatic cells and one set of pouch cells (16 cells). The first dataset, consisting of 15 cells, features cells with capacities of 0.9 Ah and 1.1 Ah, cycled at a controlled temperature of 23 °C, with standard CC-CV charging cycles. Different depths and rates of discharging/charging are evaluated. The cycles are performed until reaching 80% of the nominal capacity. The data are provided in multiple ".txt" files. The second dataset, comprising 12 cells, follows a similar format to the first one, with cells of 1.35 Ah undergoing tests at different temperatures (25 °C, 35 °C, 45 °C, and 55 °C), and various charge and discharge profiles. The data are also provided in ".txt" format. The third dataset contains 16 pouch cells, each with a capacity of 1.5 Ah, where the data were generated to assess the effects of partial charge and discharge cycles on battery capacity degradation. The temperature in all the tests is controlled at 25 °C. The data are provided in ".mat" format.

The Battery Laboratory Intelligence at the University of Oxford provides three datasets that can be explored in modeling. The first corresponds to long-term battery aging tests, featuring eight cells of 740 mAh, maintained at a controlled temperature of 40 °C. The cells were subjected to a CC-CV charging profile, followed by a discharge profile obtained from the Artemis urban profile. The data are stored in ".mat" format. The second dataset contains data from six cells of 16 Ah, collected from a one-year experiment, following real-world usage profiles of grid-connected battery applications. The data are provided in ".csv" format. The third dataset contains long-term data from 12 cells of 3 Ah, aiming to study the influence of the usage history dependence on the cell degradation. Four groups of three cells each were subjected to combined charging profiles comprising fixed calendar periods and cyclic aging applied in various orders. Cells in groups 1 and 2 were subjected to one day of cycling followed by five days of aging at C/2 and C/4, respectively. Cells in groups 3 and 4 were subjected to two days of cycling followed by ten days of aging at C/2 and C/4, respectively. The tests are conducted at a controlled temperature of 23 °C. The data are available in ".txt" format.

The dataset presented by the Beijing Institute of Technology (BIT), as introduced in study [384], consists of 77 batteries of 2.4 Ah cycled with fixed or arbitrary current profiles. Twenty-two batteries were cycled with fixed current profiles for both charging (1C, 2C, or 3C) and discharging (1C, 2C, or 3C). Fifty-five batteries were cycled with arbitrary usage profiles for charging (following a uniform distribution between 1C, 2C, or 3C and randomly changing every five cycles) and a specified discharge current (3C). The data are provided in ".csv" format.

The dataset from Stanford University, collected at the Stanford Energy Control Laboratory, was created in 2022 and is presented in [396]. It consists of 10 $LiNiMnCoO_2$/graphite cells, model INR21700-M50T, with a capacity of 4.85 Ah. For the tests, the cells were maintained at 23 °C and charged according to the CC-CV protocol, with charging rates of C/4, C/2, 1C, and 3C. The discharge aging experiments were designed to simulate a typical driving pattern of electric vehicles in the form of the Urban Dynamometer Driving

Schedule (UDDS), reducing the battery's SoC from 80% to 20%. The files are provided with ".xlsx" and ".mat" extensions.

Three datasets are provided by the Center for Electrochemical Energy Storage Ulm–Karlsruhe. They originated in 2022, using sixty-six NCA cells (3.5 Ah) in dataset 1, fifty-five NCM cells (3.5 Ah) in dataset 2, and nine NCA-NCM cells (2.5 Ah) in dataset 3. The cells in datasets 1 and 2 were maintained at controlled temperatures of 25 °C, 35 °C, and 45 °C, while the cells in dataset 3 were kept at 25 °C. The charging process of the cells followed the CC-CV protocol, with rates of 0.25 C, 0.5 C, and 1C, and with constant discharges of 1C. The files are provided with a ".csv" extension.

The dataset provided by Underwriters Laboratories, Inc. at Purdue University consists of 35 NCA cells. Of this dataset, 21 cells are cylindrical-type lithium-ion 18650, cycled at 0.5C between 2.7 and 4.2 V (0–100% SoC) at room temperature, to various levels of capacity reduction (10%, 15%, and 20%). The remaining 14 cells are pouch-type, cycled at 1C between 2.7 and 4.2 V (0–100% SoC), also at room temperature, with capacity reductions of 10–20%. The data are provided in ".csv" format.

The data provided in July 2023 by UNIBO Powertools corresponds to cycling experiments of 27 batteries, considering the use of batteries from different manufacturers, cells with various nominal capacities, and cycling conducted until the end of the cell's life, producing data at different stages of the lifespan. Three types of tests were conducted: (i) a standard test, where the battery was discharged at a current of 5 A in the main cycles; (ii) a high-current test, where the battery was discharged at a current of 8 A in the main cycles; (iii) a pre-conditioned test, where the battery cells are stored in environments at 45 °C for 90 days before conducting the test. The charging process is CC-CV at 1.8 A and 4.2 V (a 100 mA cutoff point). The data are provided in ".csv" format.

The dataset provided by Cambridge University corresponds to the work developed in [397], where continuous charge and discharge cycles were conducted on 12 lithium-ion cells Eunicell LR2032 ($LiCoO_2$/graphite), with a capacity of 45 mAh. The cells were cycled at controlled temperatures of 25 °C, 35 °C, and 45 °C. Each cycle consists of a CC-CV charge at a rate of 1C up to 4.2 V and a CC discharge at a rate of 2C up to 3 V. Electrochemical impedance spectroscopy (EIS) is measured at nine different stages of charging/discharging during each even-numbered cycle, in the frequency range from 0.02 Hz to 20 kHz, with an excitation current of 5 mA, following a 15 min open-circuit period at 0% SoC and 100% SoC. The dataset is provided in multiple ".txt" files.

The data from the University of Hawaii System correspond to two datasets, each composed of nine cells, one of type LFP, with a capacity of 1.1 Ah (APR18650M1B), and the other of type NMC, with a capacity of 3.5 Ah (INR18650MJ1). The cells were cycled under different protocols, with temperature controlled between −15 °C and 55 °C. Charging processes were of the CC-CV type, with rates of C/25 and 1C, and continuous discharges of C/25, C/5, and 1C. The details about the dataset construction can be found in [398], with the data being provided with a ".txt" extension.

The dataset provided by Carnegie Mellon University consists of 30 cylindrical cells Sony–Murata 18650 VTC-6 (3 Ah) cycled at a controlled temperature of 25 °C. The charging and discharging configurations varied, with durations ranging from 400 s to 1000 s. The data are available in ".csv" format.

3.4. Techniques and Algorithms

A survey of the techniques addressed in the papers of the bibliographic portfolio, as presented in Table 6, revealed the use of 81 distinct techniques by the authors. With 161 applications, LSTM-type DL neural networks account for approximately 22% of the techniques evaluated in the portfolio, followed by CNN-type DL networks, with 12%, and with SVM, GPR, and simple artificial neural networks (ANNs) each accounting for about 5%, which together result in almost 50% of the techniques evaluated in the non-review papers of the portfolio. Although a set of only five algorithms represents almost half of the evaluations, forty-one algorithms are evaluated only once in these studies, representing about 6% of the techniques evaluated, with a representation of 11% when techniques implemented up to three times were grouped, corresponding to fifty-six algorithms. Figure 16 presents the distribution of the techniques found in the portfolio.

Table 6. Frequency of machine-learning techniques presented in the bibliographic portfolio.

Algorithm	Frequency	Type	Algorithm	Frequency	Type
LSTM	161	Neural Network	Regressive matching network	1	Neural Network
CNN	86	Neural Network	Bls	1	Time Series
SVM	38	Kernel Method	Semi-Markov model	1	Statistical Method
GPR	37	Statistical Method	Autoregression nested sequence	1	Statistical Method
ANN	34	Neural Network	Automl	1	-
RANDOM FOREST	32	Decision Tree	Quantile regression forest	1	Quantile Regression
LINEAR REGRESSION	32	Linear Model	Sparse Bayesian learning	1	Statistical Method
ELM	31	Neural Network	Ssel	1	Time Series
RNN	29	Neural Network	Survival model	1	Survival Model
DNN	27	Neural Network	Atbls	1	Time Series
GRU	26	Neural Network	Tdnn	1	Neural Network
XGBOOST	19	Decision Tree	Transformer neural network	1	Neural Network
GRADIENT BOOSTING TREE	16	Decision Tree	Unsupervised learning	1	Unsupervised
BPNN	12	Neural Network	Unsupervised neural networks	1	Neural Network

Table 6. *Cont.*

Algorithm	Frequency	Type	Algorithm	Frequency	Type
LIGHTGBM	11	Decision Tree	Vgg11	1	Neural Network
MLP	10	Neural Network	Vision transformer network	1	Neural Network
FFNN	8	Neural Network	Quantum clustering	1	Clustering
RVM	7	Kernel Method	Deep reinforcement learning	1	Neural Network
TCN	6	Neural Network	Pknn	1	Neural Network
NAR	5	Time Series	Narxnn	1	Time Series
RIDGE REGRESSION	5	Linear Model	Densenet	1	Neural Network
ENN	5	Neural Network	Dgnn	1	Neural Network
ADABOOST	5	Decision Tree	Dilated residual network	1	Neural Network
GRAPH NEURAL NETWORK	4	Neural Network	Dsmtnet	1	Neural Network
DECISION TREE	4	Decision Tree	Efficientnet	1	Neural Network
ELASTIC NET REGRESSION	3	Linear Model	Ddan	1	Neural Network
KNN	3	Neighborhood Method	Extreme deep factorization machine	1	Neural Network
RBFNN	3	Neural Network	Fcnn	1	Neural Network
ARIMA	3	Time Series	Dcn	1	Neural Network
DBN	3	Neural Network	Fuzzy clustering	1	Clustering
DCNN	3	Neural Network	Generalized additive model	1	Statistical Method
DELM	3	Neural Network	Alexnet	1	Neural Network
LINEAR QUANTILE REGRESSION	2	Quantile Regression	Googlenet	1	Neural Network

Table 6. *Cont.*

Algorithm	Frequency	Type	Algorithm	Frequency	Type
LOGISTIC REGRESSION	2	Linear Model	Dbnn	1	Neural Network
EXTRATREES	2	Decision Tree	Crnn	1	Neural Network
BOOTSTRAP MULTIPLE LINEAR REGRESSION	2	Linear Model	Induced ordered weighted averaging	1	Statistical Method
BNN	2	Neural Network	Lasso regression	1	Linear Model
K-MEANS	2	Clustering	Cdtsgann	1	Neural Network
RESNET	2	Neural Network	Capsnet	1	Neural Network
CATBOOST	2	Decision Tree	Genetic models	1	Genetic Algorithm
BMA	1	Statistical Method			

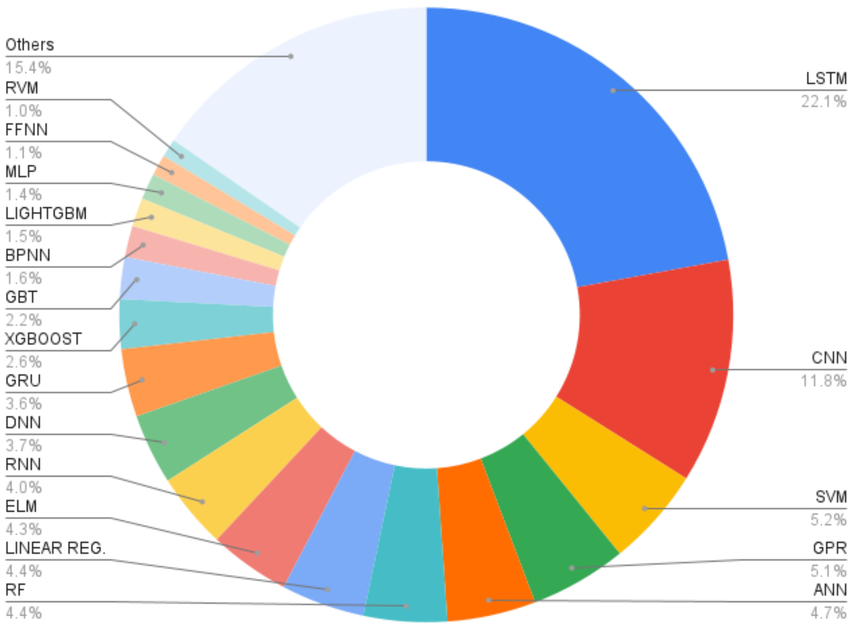


Figure 16. Frequency of ML algorithms presented in the BP.

When analyzing the algorithms implemented in the portfolio, grouped according to their category of origin, the use of techniques based on neural networks reaches the significant mark of 66% of the implementations, followed by decision-tree-based algorithms (including tree ensembles), with about 12%. Kernel methods, probabilistic statistical models, and linear regressions each account for approximately 6% of the implementations found. This analysis is presented in Figure 17.

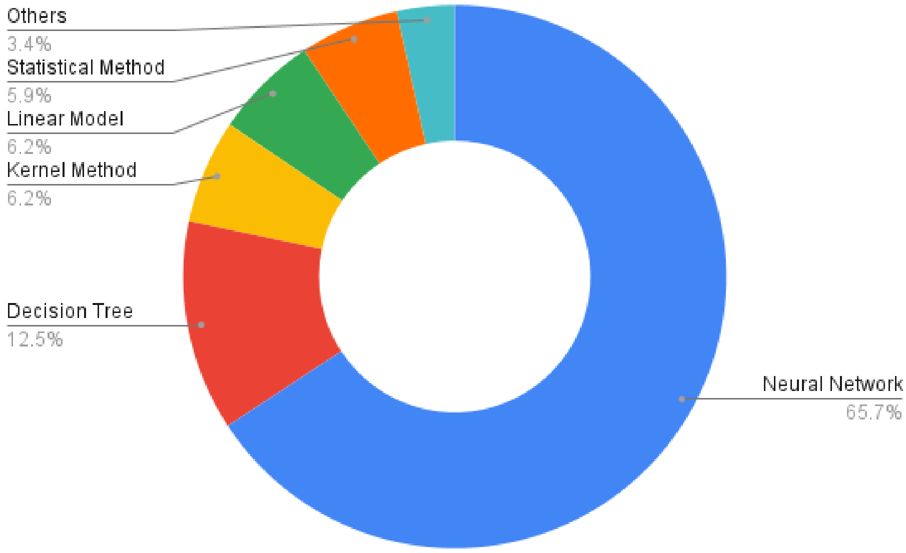


Figure 17. Frequency of groups of ML algorithms presented in the BP.

Excluding the use of neural networks, tree-based methods have gained considerable representation in the portfolio. Notably, ensemble methods, such as boosting, were employed in [83,272,399], along with implementations of popular boosting algorithms, like XGBoost in [262,400,401], LightGBM in [402–404], and CatBoost in [405,406], which have gained prominence in the field of tabular data prediction in recent studies. The use of bagging can be identified in the implementation of decision-tree ensembles, such as random forest, as explored in studies [47,161,407]. Kernel-based methods, such as SVMs, can be classified as algorithms belonging to a classical and dated approach [408], yet they were considerably analyzed in the portfolio in studies [323,409,410]. The use of classical and highly interpretable linear regression was explored in 45 studies, among which, notable studies include those presented in [1,80,146,238,321,411,412].

Another approach of relative importance corresponds to algorithms that are a part of statistical methodologies, where, out of the 43 implementations in the portfolio, 37 corresponded to the use of the GPR algorithm, with examples of implementations and analyses found in [329,369,413–415]. As presented below, the GPR algorithm demonstrated significant usage in hybrid methodologies, ranking sixth in usage within the portfolio when considering hybridized algorithms. Another point worth noting is the interpretation conducted by studies that sought to analyze degradation through classical time-series approaches, as presented in [79], which implements the ARIMAX (AutoRegressive Integrated Moving Average Model with eXogenous input) method, and in study [416] using the ARIMA (AutoRegressive Integrated Moving Average Model) method. The NAR (Nonlinear Autoregressive) model is explored in [64].

The evolution of algorithmic categories throughout the horizon comprising the bibliographic portfolio is presented in Figure 18. It is worth noting that the authors consistently focused on exploring neural network implementations throughout the entire time horizon, with the difference from other categories maintaining a growing profile. It is possible to observe a significant increase in the implementation of decision-tree-based algorithms from 2022 to 2023. The implementation of linear models has also been gaining momentum, mainly because of the comparisons that these simpler models can offer compared to more complex algorithms. Additionally, they present greater interpretability of variables and, therefore, of the modeling [6,104,417]. The use of time-series techniques has remained relatively constant in the portfolio, which, in contrast to the increasing volume of publications per year, indicates that the percentage of implementation compared to that of other categories has been decreasing. Algorithms related to clustering, quantile regression, the neighborhood method, and unsupervised learning were more recently implemented within the portfolio, between 2022 and 2023.

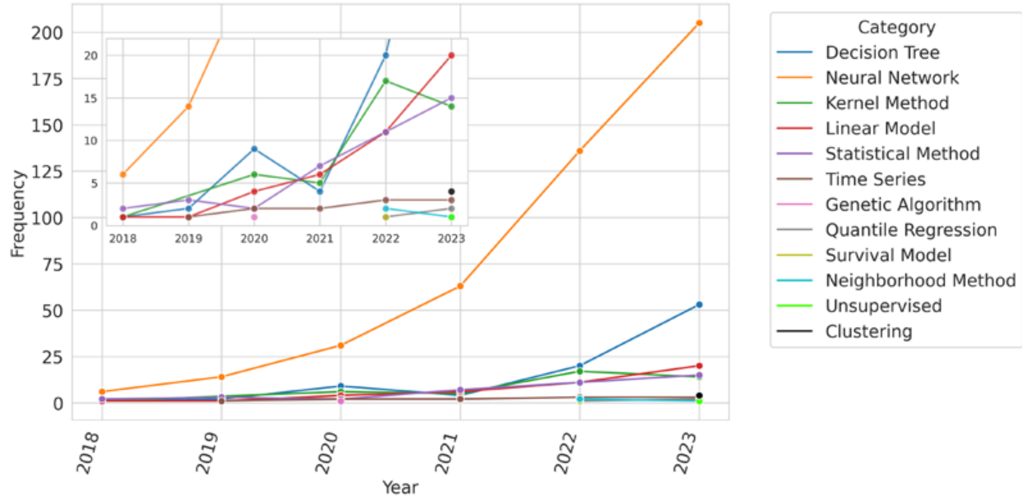
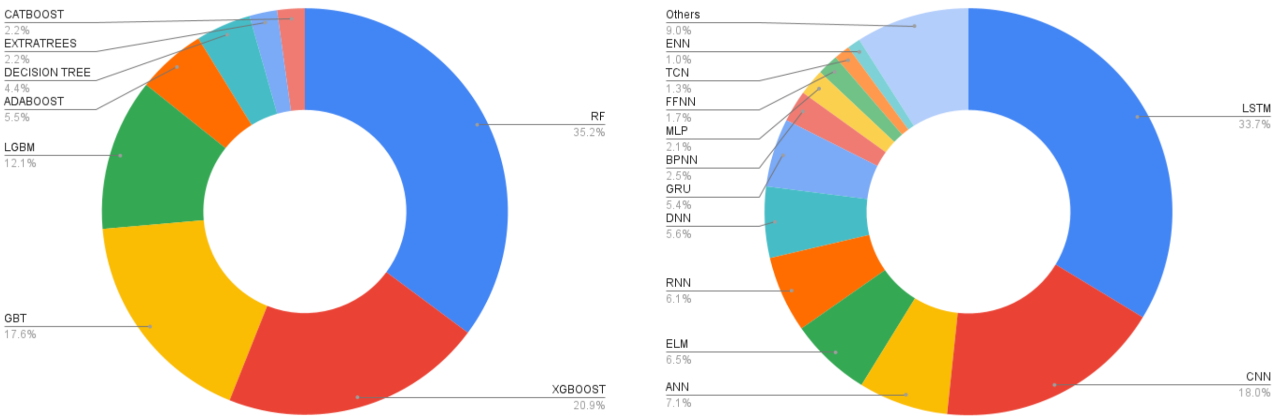


Figure 18. Evolution of algorithmic implementation in the BP by category.

Going deeper into the analysis of the two main categories of algorithms implemented in the portfolio, the graphs in Figure 19 depict the distributions of neural network and decision-tree algorithms. In the neural network category, following the observations from the overall analysis, there is a dominance of LSTM and CNN networks, followed by simple neural networks, algorithms based on well-known networks, such as extreme-learning machines and RNNs. In the decision-tree algorithms, there is a predominance of ensemble bagging using the random forest algorithm, accounting for 35% of the tree implementations in the portfolio, followed by boosting algorithms, such as XGBoost, GBT, LGBM, and Adaboost. A detailed exploration of this type of ensemble can be observed in battery degradation studies, with approximately 60% of the tree implementations in the portfolio.



(**a**) (**b**)

Figure 19. Frequencies of implemented algorithms: (**a**) decision trees; (**b**) neural networks.

When analyzing the evolution of techniques implemented in the portfolio, as depicted in Figure 20, it is noticeable that the use of LSTM networks predominates throughout almost the entire analyzed time horizon. The use of CNN networks began to gain prominence from publications in 2021. The use of the random forest became the third most implemented technique in the portfolio's works in 2023; however, the use of simple ANNs showed a sharp decline in the last year. Implementations of the SVM method seem to be decelerating, with a decrease in usage in 2021 and maintaining the number of implementations in 2023 compared to 2022. The use of GRU networks also appears to be trending, becoming the fourth most implemented algorithm in 2023. As a baseline and comparative algorithm, linear regression also demonstrates an increase in the number of implementations over the horizon. Other algorithms that seem to be experiencing a growing exploration are DNN, GPR, and XGBoost.

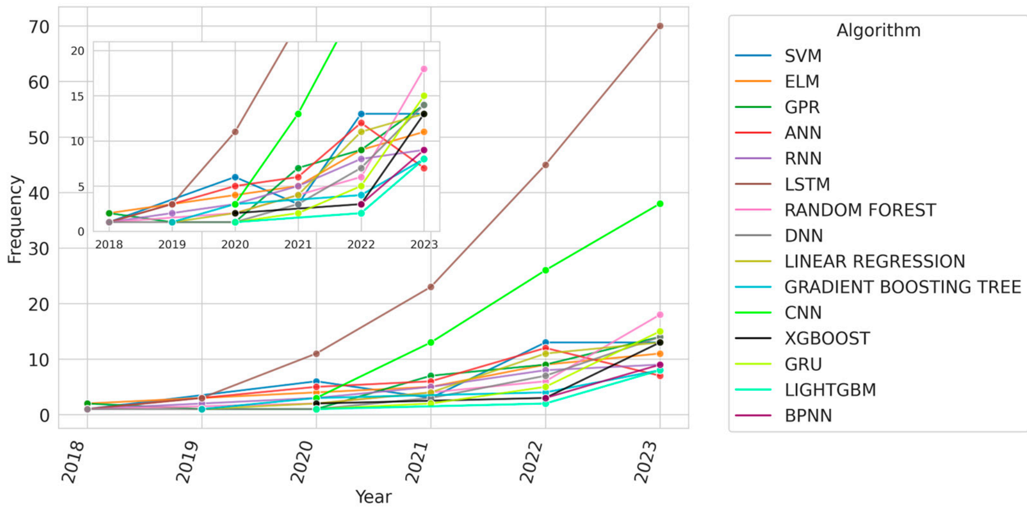


Figure 20. Evolution of algorithmic implementation in the bibliographic portfolio.

The evolution of the portfolio's main neural network implementations is presented in the graph in Figure 21. As previously highlighted, the use of LSTM and CNN networks is at the forefront of authors' research in the field, with LSTM networks being the main technique in this category from 2020 onward, and CNNs gaining prominence from 2021. It is noteworthy to highlight some recent jumps in implementations in the portfolio, from 2022 to 2023, such as the exploration of GRU, DNN, ELM, and BPNN techniques. It is striking to see the resurgence of the exploration of more classical networks, such as BPNNs, by authors in the field.

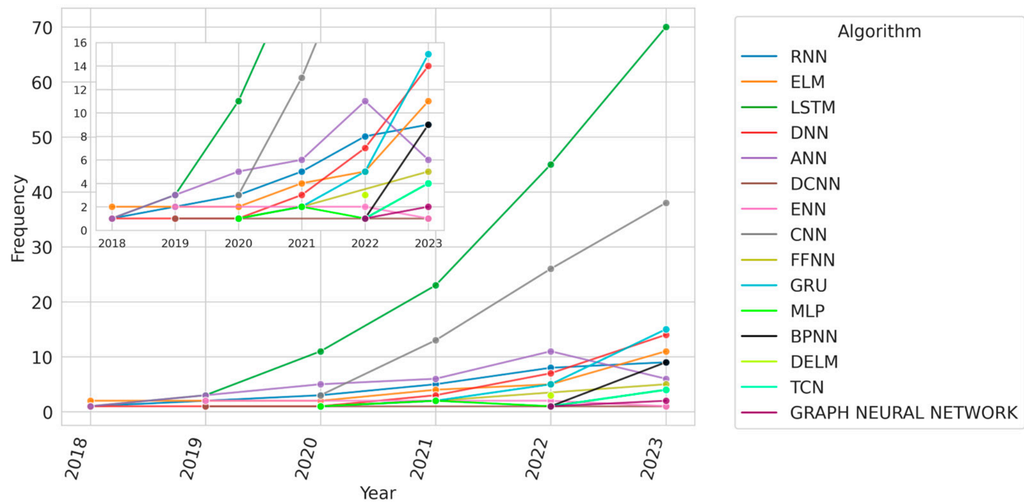


Figure 21. Evolution of neural network algorithmic implementation in the BP.

Because of its secondary prominence in the portfolio, we also present the evolution of decision-tree-based algorithms in Figure 22. The evolution of the random forest algorithm's usage over the years can be observed, with a notable increase in 2023, and the possible replacement of GBT boosting by newer versions, such as XGBoost and LightGBM.

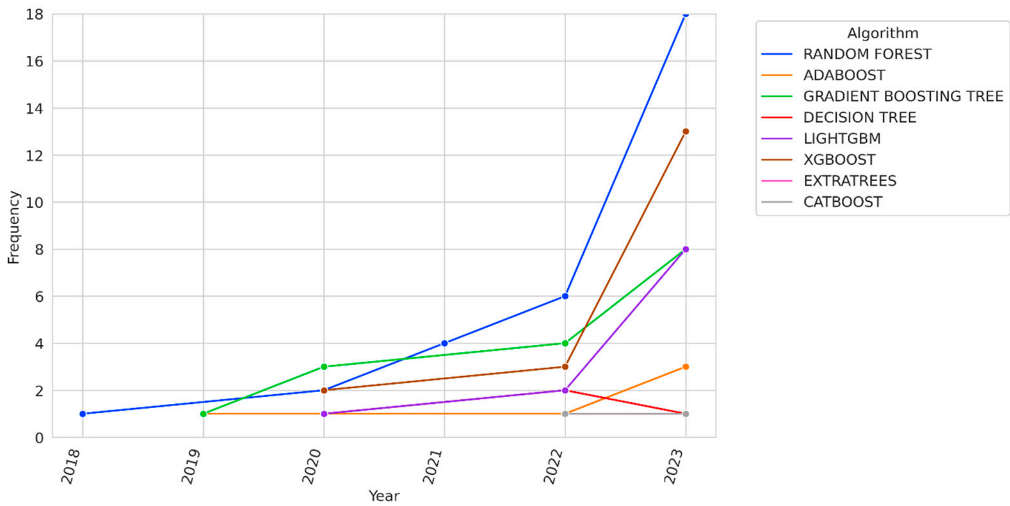


Figure 22. Evolution of decision-tree-based algorithmic implementation in the portfolio.

3.4.1. Deep-Learning Models

ML, as a subfield of artificial intelligence, employs algorithms and statistical techniques to construct predictive models. Neural networks represent a subset of ML algorithms that have seen their structural complexity increase over time, in tandem with computational advancements. This complexity primarily manifests in the augmentation of intermediate layers within networks, enhancing the algorithm's ability to discern patterns and giving rise to a subfield known as DL algorithms [418,419]. Traditional ML algorithms often outperform DL methods in scenarios of limited data availability. However, as datasets expand, traditional ML algorithms tend to reach performance plateaus, while DL algorithms demonstrate significant superiority over other learning strategies [418].

The expected potential of DL techniques can be observed in the bibliographic portfolio. Within the set of techniques belonging to neural-network-based algorithms, 307 papers using DL algorithms were identified, representing a significant 57.5% of the portfolio. This demonstrates a strong trend within this research field. DL algorithms were considered as those with more than three hidden layers. Although there is no consensus among authors and researchers in the field regarding the exact number of layers required to characterize a network as DL, some references consider this number of layers to indicate "light" DL networks, while "heavy" DL networks can have from tens to hundreds of hidden layers [420,421].

A comparative analysis of the evolution of the proportion of DL usage in neural network algorithms is shown in Figure 23. There is noticeable stability in the proportion, discounting the factor of publication volume in the early years, which settles between 80% and 90% in the last 3 years of the portfolio.

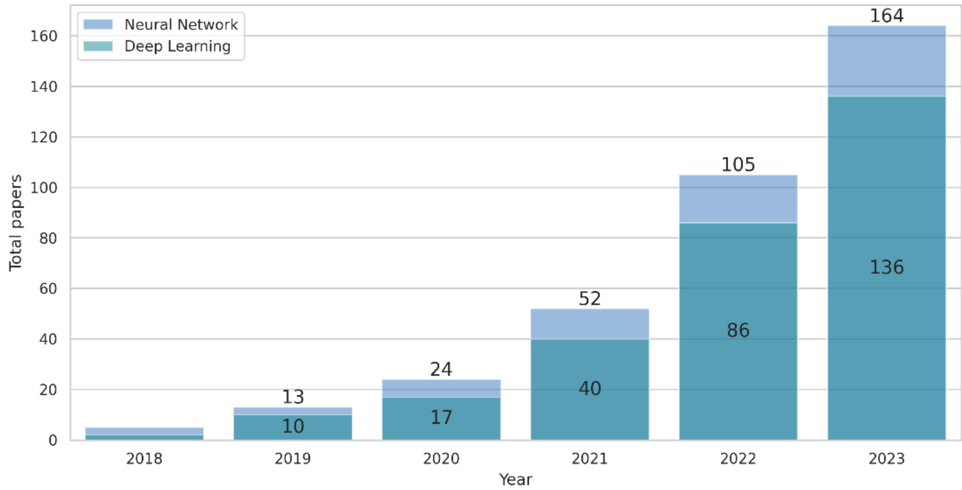


Figure 23. Proportion of DL implementation in neural network techniques in the portfolio.

The volume of DL technique implementations in the portfolio is presented in Table 7, with a visual proportion overview shown in Figure 24. In Table 7, the term "Frequency" refers to the number of implementations recorded for each technique. Papers in the portfolio may present more than one implementation within the same study. Together, LSTM and CNN techniques account for 60% of the implementations, while RNN, DNN, and GRU techniques stand out, with implementations in more than 20 papers each. In total, 23 techniques were implemented only once.

Table 7. Survey of DL techniques implemented by authors in the bibliographic portfolio.

Algorithm	Frequency	Algorithm	Frequency	Algorithm	Frequency
LSTM	161	RESNET	2	PKNN	1
CNN	86	ELM	2	DBNN	1
RNN	29	BPNN	2	DSMTNET	1
DNN	27	EFFICIENTNET	1	DCN	1
GRU	26	CRNN	1	DDAN	1
ANN	10	VISION TRANSFORMER NETWORK	1	DEEP REINFORCEMENT LEARNING	1
MLP	8	VGG11	1	DELM	1
TCN	6	TRANSFORMER NEURAL NETWORK	1	GOOGLENET	1
ENN	5	TDNN	1	DENSENET	1
FFNN	5	BNN	1	ALEXNET	1
GRAPH NN	4	CAPSNET	1	EDFM	1
DBN	3	REGRESSIVE MATCHING NETWORK	1	DILATED RESIDUAL NETWORK	1
DCNN	3	CDTSGANN	1	FCNN	1

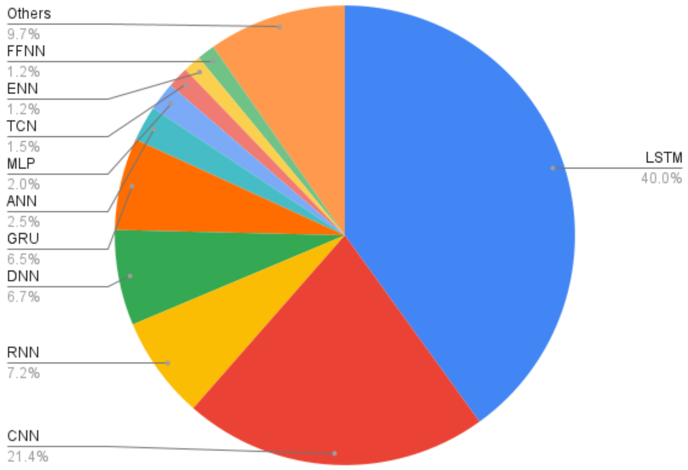


Figure 24. Distribution of techniques in DL implementations in the portfolio.

The evolution of the main DL algorithms implemented in the portfolio is presented in Figure 25, which shows that the most implemented algorithm is the LSTM network. In addition to the rising trends of LSTM and CNN networks, we again highlight the recent implementation trends of DNN and GRU algorithms, as well as the first relevant implementations of the DCNN algorithm, found in 2023, which combines characteristics of DNN and CNN networks.

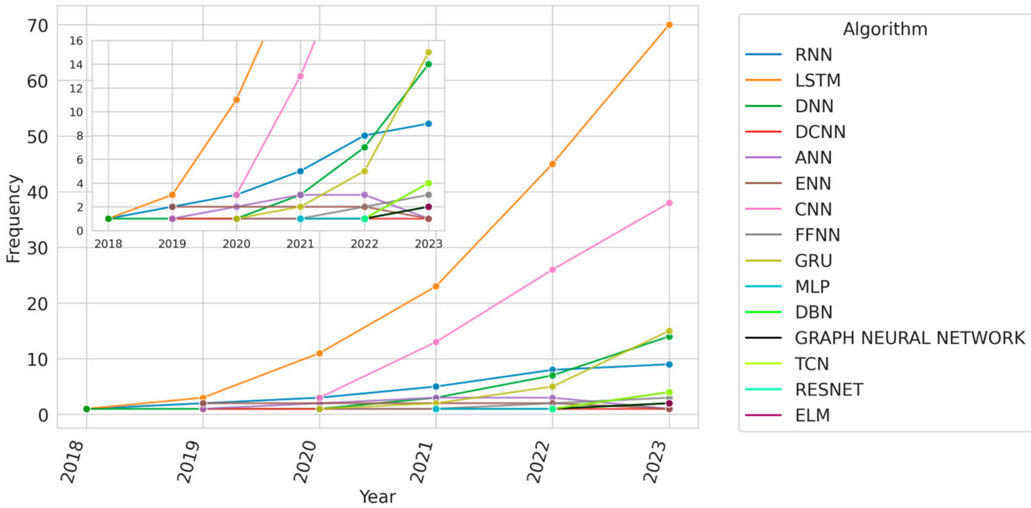


Figure 25. Evolution of DL algorithmic implementation in the BP.

In [44], which is the main DL publication according to the citation count, the authors employ a hybrid LSTM-RNN model to capture long-term information regarding the relationship between a battery's capacity and its degradation, emphasizing that such a dual approach is recommended to avoid overfitting issues. Another work utilizing a hybrid technique based on LSTM is presented in [48], using an Elman neural network (ENN). The concept of transfer learning, which involves the use of neural networks trained and fine-tuned in large datasets and then fine-tuned on their final layers in a specific dataset to transfer knowledge to another problem, is discussed in [65], which implements an LSTM network. Other examples of studies using LSTMs can be found in [51,59,422,423].

Regarding relevance by citation count, the main studies using DL are presented in Table 8, where it is notable that the use of LSTM is present in six out of the ten studies. Another interesting point is the use of a hybrid approach by the publications, using two DL algorithms in this case. The table also highlights the datasets used by the authors, with half the publications utilizing public data Additionally, the table includes a marking to indicate whether the implementation was hybrid, where more than one algorithm was used to determine the same prediction.

Table 8. Main publications in the portfolio with DL implementation.

Algorithm	Hybrid	Dataset	Title	Year	Cited	Ref.
LSTM, RNN	Yes	Author	Long short-term memory recurrent neural network for remaining-useful-life prediction of lithium-ion batteries	2018	880	[44]
LSTM, GPR	Yes	Author	A data-driven approach with uncertainty quantification for predicting future capacities and remaining useful life of lithium-ion batteries	2021	434	[45]
LSTM, ENN	Yes	Author	Remaining-useful-life prediction for lithium-ion batteries based on a hybrid model combining the long short-term memory and Elman neural networks	2019	316	[48]
DNN	No	NASA	Remaining-useful-life prediction for lithium-ion batteries: A deep-learning approach	2018	313	[49]
CNN, LSTM	Yes	NASA	A data-driven auto-CNN-LSTM prediction model for lithium-ion-batteries' remaining useful life	2021	291	[50]
LSTM	No	NASA	State-of-health estimation and remaining-useful-life prediction for lithium-ion batteries based on a variant long short-term memory neural network	2020	284	[51]
DCNN	No	Author	A deep-learning method for online capacity estimation of lithium-ion batteries	2019	260	[53]
DNN	No	CALCE, NASA, MIT, OXFORD	Machine-learning pipeline for batteries' state-of-health estimations	2021	246	[54]
LSTM	No	NASA	A neural-network-based method for RUL prediction and SOH monitoring of lithium-ion batteries	2019	245	[55]
PKNN	No	Author	A novel estimation method for the states of health of lithium-ion batteries using a prior-knowledge-based neural network and a Markov chain	2019	239	[56]

The five most recent studies with DL implementation in the bibliographic portfolio are presented in Table 9. The publications correspond to the year 2024, which, in total, had 17 publications on the subject in the first two weeks of the year (the total number of portfolio publications in 2024 was 21). The five highlighted papers make use of public datasets (16 out of 17 in total for the year), with two publications implementing a hybrid approach with DL (seven out of seventeen in total for the year), including the use of a decision-tree-based algorithm.

Table 9. Recent publications in the portfolio with DL implementation.

Algorithm	Hybrid	Dataset	Title	Year	Cited	Ref.
GCN	No	NASA, OXFORD	State-of-health and remaining-useful-life predictions of lithium-ion batteries with a conditional graph convolutional network	2024	2	[179]
RNN	No	MIT	Jellyfish-optimized recurrent neural network for state-of-health estimations of lithium-ion batteries	2024	2	[336]
LSTM	No	NASA, CALCE	Remaining-useful-life predictions of lithium Batteries based on a CNN–Mogrifier LSTM-MMD	2024	1	[192]
MLP, GRU	Yes	NASA, CALCE	An MLP–mixer and mixture of expert models for remaining-useful-life predictions of lithium-ion batteries	2024	0	[220]
RF, GRU	Yes	NASA	State-of-health estimations for lithium-ion batteries using a random forest and a gated recurrent unit	2024	0	[221]

3.4.2. Hybrid Models

Hybrid ML models combine different ML techniques and algorithms to enhance prediction performance by leveraging the strengths of each method while compensating for their individual weaknesses [48,424]. Within the bibliographic portfolio, a total of 135 publications have implemented this approach. The evolution of hybrid model usage in the portfolio is depicted in Figure 26. As shown, it can be inferred that the use of hybrid approaches in SoH estimation is a recent field of exploration, with a significant increase in implementations in 2023. Considering the volume of portfolio publications, the use of hybrid approaches represents approximately 30% of the papers surveyed, a jump of nearly 50% compared to 2022, where it was present in about 18% of publications. In the first two weeks of 2024, a total of nine papers with hybrid approaches were published.

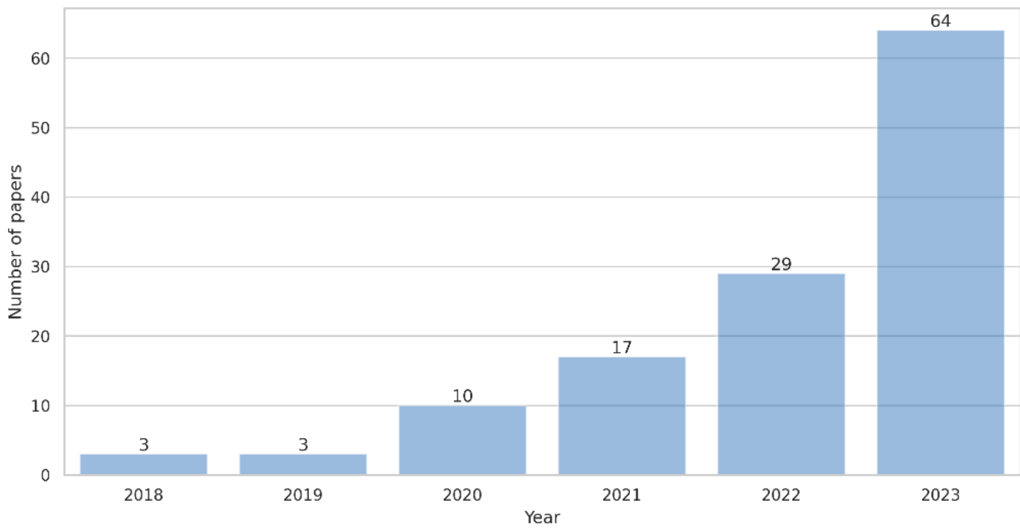


Figure 26. Evolution of hybrid algorithmic implementation in the BP.

The most utilized techniques in the hybrid modeling approach also correspond to the use of DL networks, such as LSTM and CNN, with a considerable advantage, with 74 and 51 implementations, respectively, as indicated in Figure 27. Other DL algorithms, such as GRU and RNN, are also notable, for example, in [232,233,381,425]. Other classical algorithms, such as SVM and GPR, found in [149,426], and decision-tree-based algorithms, like RF, XGBoost, and LightGBM, present in [80,221,427], are also noteworthy.

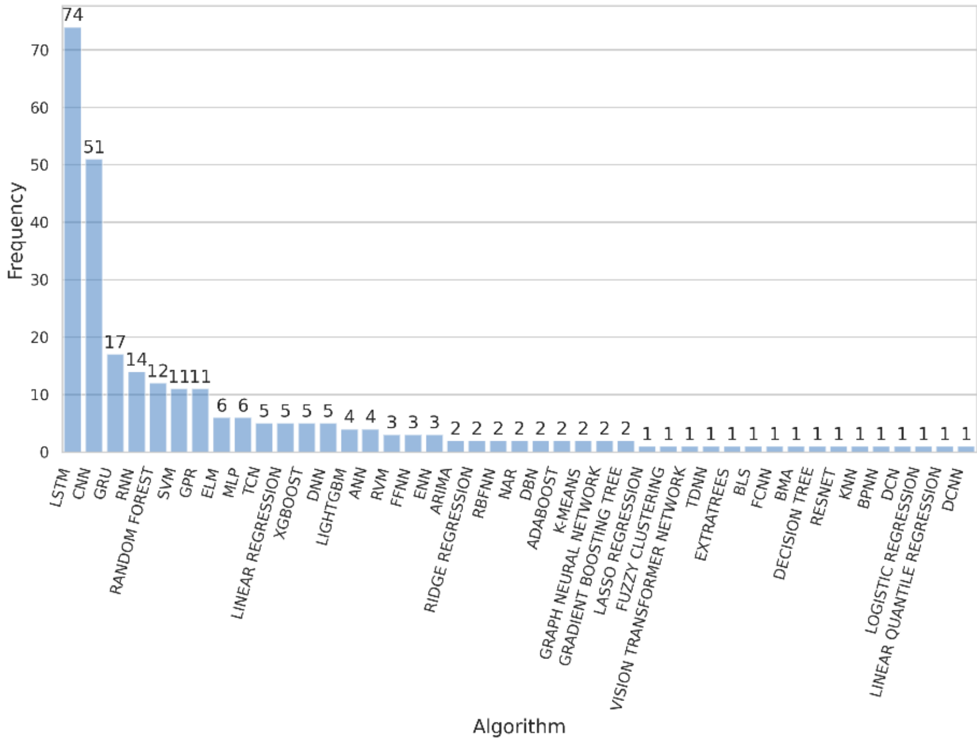


Figure 27. Frequency of techniques addressed in papers with hybrid algorithms in the BP.

The evolution of the implementations of the main algorithms is presented in Figure 28. It is possible to observe the increases in the implementations of LSTM and CNN networks, in line with previous results, and the recent evolution of the use of GRU and RF algorithms, with a peak in usage in 2023.

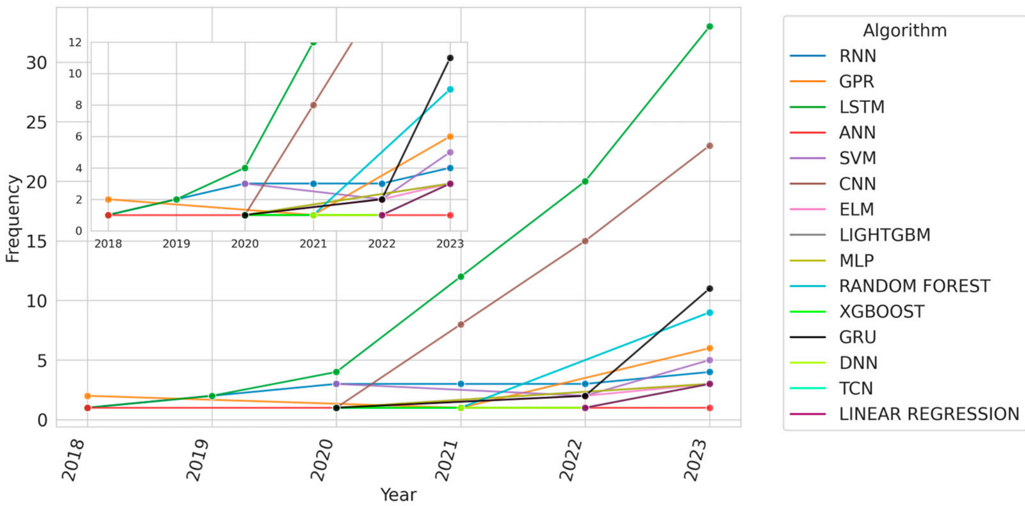


Figure 28. Evolution of hybrid algorithmic implementation in the bibliographic portfolio.

Figure 29 presents the found combinations resulting from the analysis of hybrid algorithms in the portfolio. The primary combination occurs with the LSTM and CNN networks, with 27 implementations in the portfolio. Algorithms that appear individually in the survey reflect either a hybrid approach (e.g., the integration of different configurations of the same algorithm, such as combining a 2-dimensional CNN with a 3-dimensional CNN), or methodologies that incorporate filters (e.g., the Kalman filter) and optimization algorithms as a part of their design. In total, 65 papers presented combinations of algorithms that were implemented only once in the portfolio, indicating that many researchers still evaluate different approaches of hybrid models.

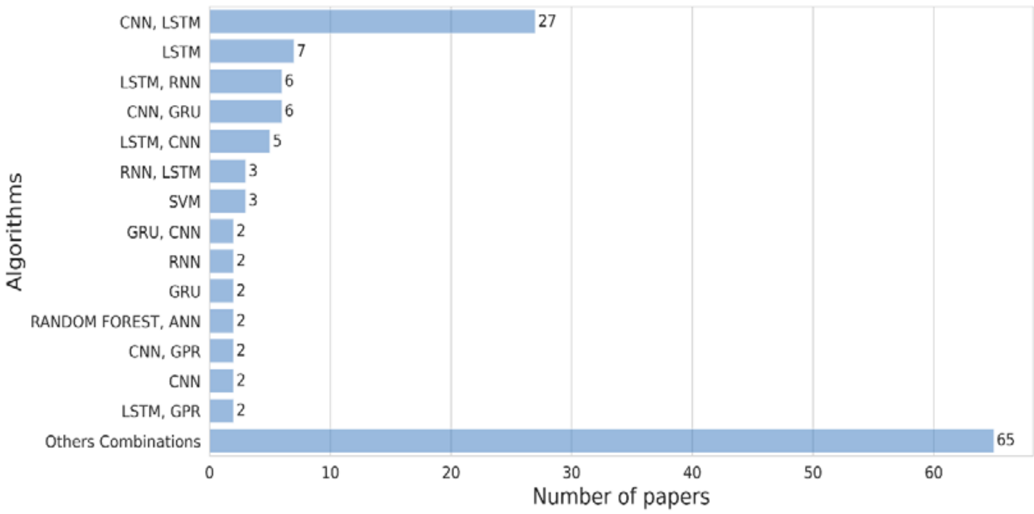


Figure 29. Combinations of algorithms found in papers with a hybrid approach in the BP.

The combinations of each algorithm in the portfolio are presented in Table 10, allowing for the identification of hybrid approaches, evaluated by the authors, within the portfolio, which can serve as a starting point for testing hybrid models in new research. A visualization of these combinations is shown in Figure 30, where centers of algorithmic connections can be observed, revolving around LSTM, CNN, RF, and GPR techniques. As demonstrated in Table 10 and Figure 30, LSTM networks exhibit a considerable range of combinations with other algorithms, including decision-tree, statistical, kernel, neighborhood, and clustering algorithms, as well as other neural network architectures.

Table 10. Connections between algorithms in papers with a hybrid approach in the BP.

Algorithm	Algorithmic Connections
LSTM	DCNN, FFNN, CNN, ANN, ENN, DNN, TCN, RNN, XGBOOST, BMA, GRAPH NEURAL NETWORK, SVM, GPR, DBN, GRU, RANDOM FOREST, FUZZY CLUSTERING, BPNN, LINEAR QUANTILE REGRESSION, MLP, RESNET, ADABOOST
RANDOM FOREST	ANN, NAR, LINEAR REGRESSION, GRADIENT-BOOSTING DECISION TREE, GPR, LIGHTGBM, XGBOOST, LSTM, SVM, RBFNN, RIDGE REGRESSION, KNN, GRU, EXTRATREES, ELM
SVM	ARIMA, DECISION TREE, ELM, LSTM, GPR, RBFNN, RANDOM FOREST, RIDGE REGRESSION, LINEAR REGRESSION, GRU, RNN

Table 10. *Cont.*

Algorithm	Algorithmic Connections
GRU	CNN, DNN, LSTM, RNN, TCN, MLP, RANDOM FOREST, ELM, LINEAR REGRESSION, SVM
CNN	LSTM, DNN, GRU, GRAPH NEURAL NETWORK, FCNN, GPR, FFNN, MLP, TCN, RESNET
GPR	LOGIC REGRESSION, ANN, LSTM, LINEAR REGRESSION, RANDOM FOREST, GRADIENT-BOOSTING DECISION TREE, CNN, SVM, RBFNN, RIDGE REGRESSION
XGBOOST	LSTM, LIGHTGBM, MLP, LASSO REGRESSION, RANDOM FOREST, KNN, RIDGE REGRESSION, GRADIENT-BOOSTING DECISION TREE, EXTRATREES, LINEAR REGRESSION
LINEAR REGRESSION	RANDOM FOREST, GRADIENT-BOOSTING DECISION TREE, GPR, LIGHTGBM, XGBOOST, RIDGE REGRESSION, EXTRATREES, SVM, GRU
RIDGE REGRESSION	GPR, SVM, RBFNN, RANDOM FOREST, LIGHTGBM, XGBOOST, GRADIENT-BOOSTING DECISION TREE, EXTRATREES, LINEAR REGRESSION
LIGHTGBM	MLP, XGBOOST, LASSO REGRESSION, RANDOM FOREST, RIDGE REGRESSION, GRADIENT-BOOSTING DECISION TREE, EXTRATREES, LINEAR REGRESSION
GRADIENT-BOOSTING DECISION TREE	LINEAR REGRESSION, RANDOM FOREST, GPR, LIGHTGBM, XGBOOST, RIDGE REGRESSION, EXTRATREES
MLP	LIGHTGBM, XGBOOST, LASSO REGRESSION, CNN, LSTM, VISION TRANSFORMER NETWORK, GRU
EXTRATREES	LIGHTGBM, XGBOOST, RIDGE REGRESSION, RANDOM FOREST, GRADIENT-BOOSTING DECISION TREE, LINEAR REGRESSION
TCN	LSTM, GRU, DNN, DCN, CNN, RESNET
ELM	RVM, SVM, DBN, GRU, RANDOM FOREST
DNN	CNN, LSTM, GRU, K-MEANS, TCN
RNN	LSTM, NAR, TDNN, GRU, SVM
RBFNN	K-MEANS, GPR, SVM, RANDOM FOREST, RIDGE REGRESSION
ENN	ARIMA, LSTM, ADABOOST
RESNET	CNN, LSTM, TCN
ANN	LSTM, RANDOM FOREST, GPR
NAR	RNN, TDNN, RANDOM FOREST
LASSO REGRESSION	LIGHTGBM, MLP, XGBOOST
ARIMA	SVM, ENN
TDNN	NAR, RNN
RVM	ELM, BLS
DBN	LSTM, ELM

Table 10. *Cont.*

Algorithm	Algorithmic Connections
KNN	RANDOM FOREST, XGBOOST
K-MEANS	RBFNN, DNN
GRAPH NEURAL NETWORK	CNN, LSTM
FFNN	LSTM, CNN
ADABOOST	ENN, LSTM
LINEAR QUANTILE REGRESSION	LSTM
LOGIC REGRESSION	GPR
BMA	LSTM
DCN	TCN
BLS	RVM
BPNN	LSTM
FUZZY CLUSTERING	LSTM
FCNN	CNN
DECISION TREE	SVM
DCNN	LSTM
VISION TRANSFORMER NETWORK	MLP

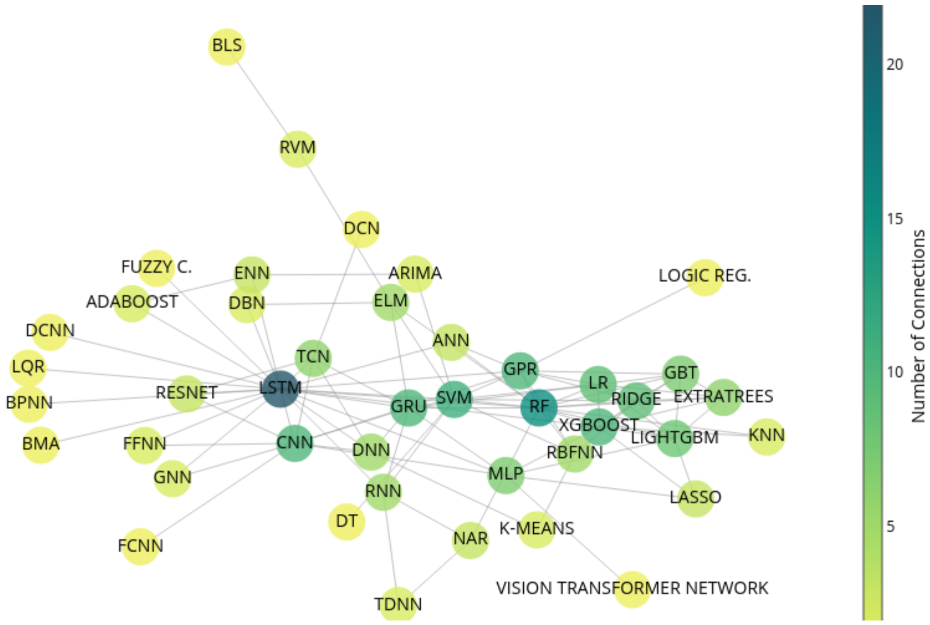


Figure 30. Connections between algorithms in papers with a hybrid approach in the BP.

Tables 11 and 12 present, respectively, the most relevant and most recent studies with hybrid modeling present in the bibliographic portfolio.

Table 11. Key publications in the portfolio with hybrid model implementation.

Algorithm	Dataset	Title	Year	Cited	Ref.
LSTM, RNN	Author	Long short-term memory recurrent neural network for remaining-useful-life predictions of lithium-ion batteries	2018	880	[44]
LSTM, GPR	Author	A data-driven approach with uncertainty quantification for predicting future capacities and the remaining useful life of lithium-ion batteries	2021	434	[45]
LSTM, ENN	Author	Remaining-useful-life prediction for lithium-ion batteries based on a hybrid model combining the long short-term memory and Elman neural networks	2019	316	[48]
CNN, LSTM	NASA	A data-driven auto-CNN-LSTM prediction model for lithium-ion-batteries' remaining useful life	2021	291	[50]
Logic Regression, GPR	NASA	State-of-health prediction of lithium-ion batteries: Multiscale logic regression and Gaussian process regression ensemble	2018	204	[60]
GRU, CNN	NASA	A novel deep-learning framework for state-of-health estimation of lithium-ion batteries	2020	203	[61]
NAR, RF	Author	State-of-health estimation and remaining-useful-life prediction for lithium-ion batteries using a hybrid data-driven method	2020	190	[64]
LSTM, RNN	Author	Deep-learning-based prognostic approach for lithium-ion batteries with adaptive time-series prediction and online validation	2020	134	[71]
3-CNN, 2-CNN	MIT	A machine-learning prediction method of lithium-ion-battery life based on charge processes for different applications	2021	113	[315]
CNN, LSTM, DNN	NASA, CALCE	Remaining-useful-life assessment for lithium-ion batteries using a CNN-LSTM-DNN hybrid method	2021	108	[236]

Table 12. Most recent publications in the portfolio with hybrid model implementation.

Algorithm	Dataset	Title	Year	Cited	Ref.
SVM, RNN	NASA CALCE	Data-driven transfer-stacking-based state-of-health estimation for lithium-ion batteries	2024	14	[270]
RF, GRU	NASA	State-of-health estimation for lithium-ion batteries using a random forest and a gated recurrent unit	2024	0	[221]
CNN, GPR	Author	Probabilistic lithium-ion-batteries' state-of-health predictions using convolutional neural networks and a Gaussian process regression	2024	0	[414]

Table 12. *Cont.*

Algorithm	Dataset	Title	Year	Cited	Ref.
CNN, LSTM, TCN, RESNET	Author	A machine-learning framework for remaining-useful-lifetime prediction of Li-ion batteries using diverse neural networks	2024	0	[428]
CNN, GRU	NASA	Lithium-ion-batteries' state-of-health estimations using a hybrid model based on a convolutional neural network and a bidirectional gated recurrent unit	2024	0	[223]

Among the most relevant studies, the use of LSTM or CNN was present in seven out of the ten papers. This predominance is expected, given the previous findings; however, the presence of these algorithms in the hybrid models for the highly cited papers also demonstrates that their implementation leads to promising results in SoH estimation. A similar perspective occurs in the analysis of the most recent studies, indicating that researchers continue to develop hybrid models around these neural network architectures. As shown further ahead, the performance of studies that employed hybrid approaches sometimes yielded superior results compared to the use of simple models, as was the case in [335], which used GPR with LSTM and managed to reduce MAPE levels by approximately 50% compared to those in [1].

3.4.3. Transfer-Learning Models

Transfer-learning (TL) techniques involve the process where a model trained in a particular primary dataset is reused as a starting point to train a new model in a new dataset [429–431]. In this case, the knowledge from the model obtained from the first dataset can be transferred to the model with the second dataset. This technique is especially useful when the second dataset is limited in volume or when training a model from scratch presents a high computational cost [429–431]. This principle is widely used in tasks in the areas of computer vision and natural language processing [429–431].

Given that data for estimating the health state of a battery require experimental effort (e.g., the programming of generalist tests, cycling processes until their end of life, and data collection), which, in turn, takes time, the use of TL within this research field can be useful for leveraging the volume of available open data, as well as aggregating new data collected in a cycle of studies, and, thus, transferring learning to more customized datasets. This idea was found in 42 publications, as shown by the annual evolution in the graph in Figure 31 (two publications belong to the year 2024). The emergence of this learning method only occurred in 2020 within the portfolio, with the years 2022 and 2023 being the main publication years.

The survey of ML techniques employed in these publications mainly identified the use of LSTM networks, which accounts for approximately 40% of the implementations, as shown in Figure 32. Also noticeable is the use of decision-tree-based techniques, such as in [354] with Adaboost implementation, and well-known DL networks in computer vision tasks, such as GoogleNet and ResNet, present in [110]. The key publications using TL and the most recent publications found in the portfolio are presented in Tables 13 and 14, respectively.

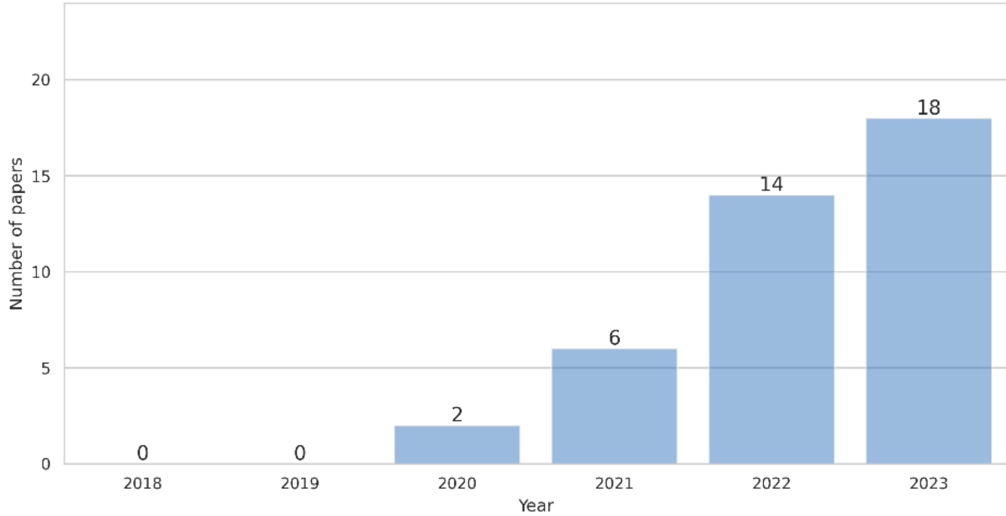


Figure 31. Evolution of TL algorithm implementation in the bibliographic portfolio.

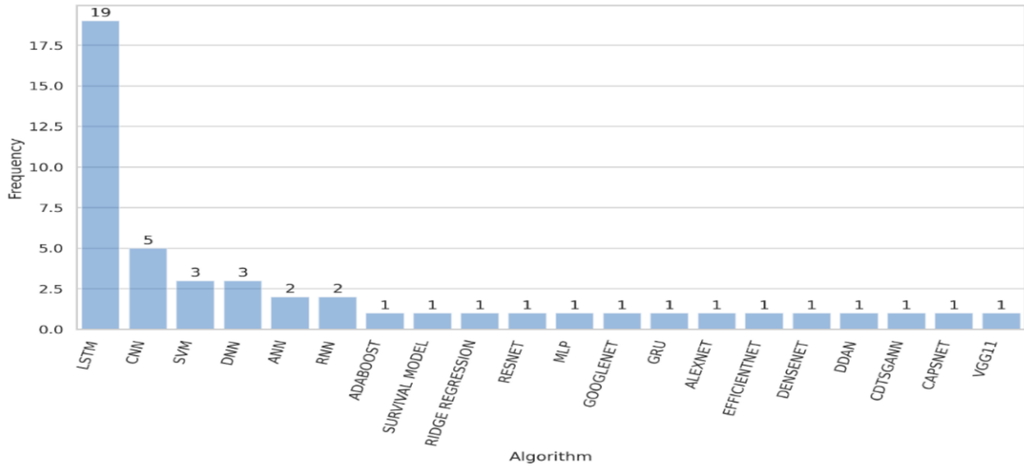


Figure 32. Frequency of techniques addressed in papers with TL algorithms in the BP.

Table 13. Key publications in the portfolio with TL implementation.

Algorithm	Dataset	Title	Year	Cited by	Ref.
LSTM	AUTHOR	Transfer learning with long short-term memory networks for state-of-health prediction of lithium-ion batteries	2020	184	[65]
CNN	AUTHOR	Lithium-ion-batteries' capacity estimation—A pruned convolutional neural network approach assisted by transfer learning	2021	142	[7]
GRU	MIT	Predictive battery health management with transfer learning and online model correction	2021	122	[72]
LSTM	MIT	Battery health estimation with degradation pattern recognition and transfer learning	2022	102	[316]

Table 13. *Cont.*

Algorithm	Dataset	Title	Year	Cited by	Ref.
KERNEL RIDGE REGRESSION	NASA	State-of-health estimation of lithium-ion batteries based on semi-supervised transfer component analysis	2020	100	[238]
LSTM	AUTHOR	A flexible state-of-health prediction scheme for lithium-ion-battery packs with a long short-term memory network and transfer learning	2021	81	[432]
LSTM	NASA, CALCE	Forecasting the state-of-health of lithium-ion batteries using a variational long short-term memory with transfer learning	2021	65	[249]
LSTM	AUTHOR	A hybrid transfer-learning scheme for remaining-useful-life prediction and cycle-life-test optimization of different formulations of Li-ion power batteries	2021	60	[433]
CNN	BIT	Real-time personalized health status prediction of lithium-ion batteries using deep transfer learning	2022	42	[385]
LSTM	CALCE	A long short-term memory neural-network-based Wiener process model for remaining-useful-life prediction	2022	39	[362]

Table 14. Most recent publications in the portfolio with TL implementation.

Algorithm	Dataset	Title	Year	Cited by	Ref.
SVM, RNN	NASA, CALCE	Data-driven transfer-stacking-based state-of-Health estimation for lithium-ion batteries	2024	14	[270]
LSTM	NASA	Transfer-learning-based remaining-useful-life prediction of lithium-ion batteries considering the capacity regeneration phenomenon	2024	0	[296]
-	-	Transfer learning for batteries' smarter state estimation and aging prognostics: Recent progress, challenges, and prospects	2023	32	[27]
CAPSNET	AUTHOR	Novel image-based rapid RUL prediction for Li-ion batteries using a capsule network and transfer learning	2023	9	[109]
CNN	STANFORD, BIT	Voltage-relaxation-based state-of-health estimation of lithium-ion batteries using convolutional neural networks and transfer learning	2023	4	[389]

3.5. Performance Analysis

To evaluate the performance obtained in the bibliographic portfolio, the MIT dataset, which was produced in [1], was selected. This dataset was chosen because the authors recorded the sets of cells used in the training, testing, and validation splits, thus allowing other studies to replicate the sets and conduct a fair comparison of results. However, most of the analyzed publications chose to perform different splits, making a direct comparison difficult. In these cases, the comparisons are empirical, and there is an associated probability of a particular approach being better than another. Among the arguments used are concerns related to the quality of the data from some cells, as well as supposed bias in the training split based on differences in the distribution of the cycles used in [1]. Another point that drew attention was cases where authors performed splits of training, testing, and validation while keeping data samples from all the cells in each set, which impacts the reliability of the results presented, as per the performances in the articles highlighted below.

Table 15 summarizes the RUL (remaining-useful-life) prediction performances in publications that had the same validation set, totaling five papers. The validation sets are referred to as the 1° Test and 2° Test by the authors in [1]. The 1° Test includes batteries under the same cycling conditions as those of the training set, while the 2° Test corresponds to batteries with a different usage profile. Notably, the performance gain achieved in [335] is highlighted, where the MAPE errors in both test sets are reduced by over 50% compared to that of the baseline study [1]. This improvement was achieved using the same 100 cycles of information for the prediction and implementing a hybrid model using the LSTM DL technique along with the GPR algorithm. However, such significant results were not found in the use of the LSTM-CNN combination in [333], where a range of errors similar to that of the baseline study [1] was observed despite employing more complex techniques. In [317], an increase in performance is evident with a hybrid approach involving neural networks, linear regression, and RF, using a reduced set of 80 cycles. These findings suggest that efforts in algorithmic selection do not necessarily guarantee higher performance, and steps such as feature construction and selection may represent an even more relevant stage in research.

In Table 16, the rest of the performance survey with the MIT dataset, conducted in the bibliographic portfolio, is presented. Here, the authors did not maintain the same modeling and validation splits, and there are variations in the target variables. Therefore, all the comparisons made may exhibit significant bias. The targets described in the table are presented to maintain the nomenclature adopted by the authors. The target's "early battery lifetime", also referred to in studies as the "early cycle life", aims to determine the total number of cycles a battery will present based on data from the first cycles of a battery. The "end of life" in the analyzed studies is related to determining the total number of cycles considering data from the last cycles, without necessarily knowing the entire battery history. Therefore, it is generally accompanied by models that determine the remaining number of cycles (RULs) and/or the current cycle. The "capacity" target was linked to studies that used regression models in predicting time series ("capacity trajectories"), where the evolution of the battery capacity over time is obtained or the prediction on a short horizon, such as the discharge capacity in the next cycle, can be used for SoH updates.

Table 15. Prediction performance of studies using the same samples for validation with MIT dataset.

Algorithm	1° Test		2° Test		Cycles	Title	Year	Cited	Ref.
	RMSE	MAPE	RMSE	MAPE					
Linear regression	118	14.1	214	10.7	100	Data-driven prediction of the battery cycle life before capacity degradation	2019	811	[1]
RF, linear regression, ANN	80	9.8	174	7.5	80	Prognostics of the battery cycle life in the early-cycle stage based on a hybrid model	2021	41	[317]
Ridge Reg Enet Reg RF MLP CNN	125 132 141 140 72	-	188 196 197 218 204	-	100	Statistical learning for accurate and interpretable battery lifetime predictions	2021	30	[102]
CNN, MLP	114	8.54	178	11.31	100	A hybrid ensemble deep-learning approach for the early prediction of batteries' remaining useful life	2023	9	[333]
GPR, LSTM	30	5.52	51	5.35	100	Joint modeling for early predictions of Li-ion-batteries' cycle life and degradation trajectory	2023	3	[335]

Table 16. Prediction performance of studies in the portfolio using different samples for validation with the MIT dataset.

Algorithm	Target	MAPE	RMSE	RMSPE	MAE	MRE	R^2	Observations	Ref.	Year
Bayesian ridge GPR RF DNN	Capacity (Ah)	0.45 1.00 0.11 0.23		0.76 1.91 0.14 0.45				- Predicting capacity considering only a short portion of partial charge/discharge data - Requires a 15 min sample of operation - Utilizes charging and discharging steps - 63 cells for training, 10 for calibration, 51 for testing (split based on the distribution of cycle numbers in the dataset, maintaining the same distribution across all the sets)	[54]	2021
CNN	RUL	10.6	76					- Utilization of four cycles - Incorporation of charging and discharging steps - 86 cells for training, 19 for validation, 19 for testing	[8]	2020

Table 16. *Cont.*

Algorithm	Target	MAPE	RMSE	RMSPE	MAE	MRE	R^2	Observations	Ref.	Year
GBT	RUL	7.5	84.9		58.6	0.94		- Usage of 250 cycles - Incorporation of the discharge stage - Data split into 2/3 for training and 1/3 for testing; no specification if cells from the training set are excluded from the test set; the splitting process is repeated four times, and the performances are analyzed - Performance corresponds to the average of the four cases	[83]	2020
CNN	Early battery lifetime	3.80 (1) 1.30 (2) 1.12 (3) 1.21 (4) 1.12 (5)	42 (1) 19 (2) 13 (3) 13 (4) 11 (5)		33 (1) 13 (2) 11 (3) 10 (4) 9 (5)			- Testing for the use of the first 20 (1), 40 (2), 60 (3), 80 (4), 100 (5) cycles for battery life prediction - Utilization of the first five cycles and the last fifteen cycles for RUL prediction - Incorporation of the charging stage - 94 cells for training, 30 for testing	[315]	2021
	RUL	3.55	11		9					
DNN	End of life	7.78 (1) 3.97 (2)	57 (1) 33 (2)					- Testing for the use of the last 1 (1) to 100 (2) cycles. - Incorporation of the discharging stage - EoL = current cycle + cycles used for data collection + RUL. - 65 cells for training, 16 for testing (discarding 43 cells) - Majority of RMSE for RUL < 50 cycles, larger errors for cells with fewer than 100 cycles - * Errors for predicting the current life cycle increase infinitely for cells with over 750 cycles (author's justification based on the low sample quantity for this scenario)	[318]	2022
	Cycle life		<65 (1) <40 (2) >90 *							
	RUL		<65 (1) <40 (2)							

Table 16. *Cont.*

Algorithm	Target	MAPE	RMSE	RMSPE	MAE	MRE	R^2	Observations	Ref.	Year
SVR	Capacity trajectory (Ah)	1.61		3.22				- Use of the last 20 cycles - Estimates the evolution of capacity trajectory over time until EoL (time series using regression) - Incorporation of both charging and discharging stages. - 84 cells for training, 40 for testing	[253]	2022
RF		0.93		2.12						
GPR		1.35		2.58						
ANN		1.13		1.92						
CNN	RUL	4.15	27.47		16.09			- Use of 10 cycles - Incorporation of the charging stage - 70% of the data for training, 30% for testing (does not specify if cells from the training set were excluded from testing)	[319]	2022
Linear reg, (1)	RUL		90			53.81 *		- Use of 10 cycles - Does not exclude cells from training during testing; 60% of the data for training, 20% for validation, and 20% for testing - Incorporation of the charging stage - Classification model to predict if a battery has less than 150 cycles of RUL or 150 cycles or more of RUL - RUL Approaches: - (1): Does not consider the classification model - (2): Regression model for each predicted RUL class in the classification model - * Considering cases where RUL > 150 cycles: 18.51, 10.51, 9.79, respectively - For capacity, the author evaluated 100 **, 150 ***, and 200 **** cycles ahead	[321]	2021
MLP (1)			52			23.03 *				
Logistic reg. + MLP (2)			49			15.2 *				
MLP	Discharge capacity after “x” cycles.					0.24 ** 0.45 *** 0.64 ****				

Table 16. *Cont.*

Algorithm	Target	MAPE	RMSE	RMSPE	MAE	MRE	R^2	Observations	Ref.	Year
Transfer Learning (CNN + RNN + "fully connected")	Capacity (Ah)	0.176 *	2.57 *				0.999 *	- Use of the last 30 cycles to predict the capacity of the next cycle and RUL - The author does not assess the performance of estimating the capacity trajectory for horizons longer than one cycle - Use of the charging stage - Use of the MIT dataset to train a model and evaluate the performance of the model with transfer learning on a dataset constructed by the author - Author's dataset contains information from 77 LFP/graphite cells of 1.1 Ah. - 22 cells separated for testing - * Performance considering training with the author's dataset. - ** Performance considering transfer learning from a model pretrained with the MIT dataset	[385]	2022
		0.328 **	4.65 **				0.997 **			
	RUL	8.72 *	186 *				0.804 *			
		9.80 **	240 **				0.770 **			
Elastic net	RUL	5.21	43.38				0.98	- Use of 100 cycles - Use of both charging and discharging stages - No exclusion of cells from training in testing; 70% of the data for training, 30% for testing	[329]	2022
GPR		5.26	43.71				0.98			
SVM		5.88	53.04				0.97			
RF		8.17	84.69				0.92			
DT ensemble		7.93	88.74				0.91			
XGBoost		7.92	91.13				0.92			
RVM		10.32	96.21				0.89			
DT		9.59	106.62				0.87			

Table 16. *Cont.*

Algorithm	Target	MAPE	RMSE	RMSPE	MAE	MRE	R^2	Observations	Ref.	Year
CNN, LSTM	Cycle life	2.28 (1)	19 (1)		14 (1)		0.9980 (1)	- Testing of usage from the last 50 (1), 60 (2), 70 (3), 80 (4), 90 (5), 100 (6) cycles - Usage of both charging and discharging stages - 93 cells for training and 31 for testing (split based on the distribution of cycle numbers in the dataset, maintaining the same distribution in all the sets)	[327]	2022
		4.59 (2)	50 (2)		33 (2)		0.9869 (2)			
		3.02 (3)	25 (3)		18 (3)		0.9967 (3)			
		3.43 (4)	25 (4)		19 (4)		0.9967 (4)			
		1.84 (5)	16 (5)		13 (5)		0.9985 (5)			
		1.47 (6)	11 (6)		9 (6)		0.9993 (6)			
	RUL	2.16 (1)	12 (1)		8 (1)		0.9993 (1)			
		3.17 (2)	15 (2)		12 (2)		0.9989 (2)			
		1.93 (3)	11 (3)		8 (3)		0.9994 (3)			
		1.85 (4)	14 (4)		10 (4)		0.9990 (4)			
		1.72 (5)	13 (5)		9 (5)		0.9992 (5)			
		1.25 (6)	8 (6)		6 (6)		0.9997 (6)			
Graph Neural Network	Capacity trajectory (Ah)	0.009 *			0.0377 *		0.9399 *	- Using 350 measurement points as input. - Usage of the charging stage. - 70% of the cells used for training and 30% for testing. - Estimates the evolution of capacity trajectory over time until End of Life (time series using regression). - * Performance based on the worst predicted cell. - ** Performance based on the best predicted cell.	[92]	2023
		0.004 **			0.0025 **		0.9894 **			

Table 16. *Cont.*

Algorithm	Target	MAPE	RMSE	RMSPE	MAE	MRE	R^2	Observations	Ref.	Year
LightGBM XGBoost RF SVR GPR Stacking	SoH (%)		1.751 1.616 1.721 1.926 1.539 1.489 *					- Estimation of SoH based on 300 s measurements - Usage of the discharge stage - Cells 91 and 100 from the MIT dataset are used for training, cell 124 used for testing - * Model considering LightGBM, XGBoost, Random Forest (RF), SVR, GPR as base models, and linear regression as a meta-model	[99]	2023
LSTM	SoH (%) after "x" cycles	0.016 (1) 0.021 (2) 0.024 (3) 0.024 (4) 0.031 (5) 0.026 (6) 0.030 (7) 0.032 (8) 0.033 (9)		1.81 (1) 2.30 (2) 2.80 (3) 2.86 (4) 3.60 (5) 3.00 (6) 3.49 (7) 3.70 (8) 3.80 (9)	0.0098 (1) 0.0130 (2) 0.0140 (3) 0.0120 (4) 0.0180 (5) 0.0150 (6) 0.0200 (7) 0.0200 (8) 0.0201 (9)			- Testing prediction horizons of 25 (1), 50 (2), 100 (3), 150 (4), 200 (5), 250 (6), 300 (7), 350 (8), 400 (9) cycles ahead - Usage of charge and discharge stages - 64% of the cells are used for training, 20% for validation, and 16% for testing (cells cannot be in more than one set) - Average of performances per cell	[144]	2023

Table 16. *Cont.*

Algorithm	Target	MAPE	RMSE	RMSPE	MAE	MRE	R^2	Observations	Ref.	Year
RF	Cycle life	0.57			4.65			- Usage of 100 cycles. - Utilization of charge and discharge stages. - 75% of the data used for training, 25% used for testing (cells from the training set were not excluded from testing). - Discrepant results compared to the literature, potential model validation error by the author.	[334]	2022
ResNet50	Early lifetime		119.98				0.8501	- Use of the first 100 cycles for predicting the total lifespan. - Utilization of images obtained from plots with voltage and capacity information as features. - 80 cells for training and 43 cells for testing, process repeated five times.	[111]	2024
CNN			115.85				0.8557			
LeNet			129.77				0.8197			
AlexNet			91.51				0.9121			
VGG16			122.19				0.8466			

Through a comparison analysis, it is possible to observe performance improvements compared to the baseline study in [315], with a MAPE of around 3.5% using a CNN. In [8], the authors achieved significant performance with a CNN and only four cycles of data as input to the algorithm, a reduction that provides new perspectives for the use and conditioning of batteries. Using TL, the authors in [385] achieved results within the error magnitudes of the studies that use only one dataset, demonstrating that TL can be a useful tool for aggregating the volume of information from other types of experimental tests and cell technologies to overcome data limitations. In [327], the best results for RUL prediction were achieved, with MAPE values below 2%. The authors conducted tests considering different data usage intervals, ranging from 50 to 100 cycles, and using a hybrid LSTM-CNN approach. Conversely, in [334], the authors claim errors around half a cycle, well below those presented in various consulted studies. The use of data from all the cells during training ends up bringing a possible leakage when validating the algorithm because the pattern of all the cells was passed to the model, which, consequently, did not develop proper learning but possible "rote memorization", associating levels of variable values with related life cycles. This point highlights the importance of correctly analyzing the results for the dissemination of research in the field.

This analysis reveals significant challenges in comparing RUL prediction models because of inconsistencies in data splitting, target variables, and evaluation metrics across different studies. Although advancements have been observed, particularly with hybrid models, like LSTM-GPR and the application of TL, the lack of standardized methodologies hinders direct comparisons and hinders the identification of truly superior approaches. The use of limited data cycles in training, as demonstrated in [8], and the exploration of feature engineering, as suggested by the results in [317], present promising avenues for future research. However, it is crucial to emphasize the importance of rigorous data splitting procedures, avoiding data leakage, as observed in [334], to ensure the reliability and generalizability of the obtained results. Notably, for most of the analyzed models, MAPE errors of around 10% have become achievable with the development of algorithms and open datasets. Moving forward, establishing standardized datasets and evaluation protocols will be essential to facilitate progress in the field and enable more meaningful comparisons between different RUL prediction models.

3.6. The Importance of SoH in Smart Systems, Energy Informatics, and Smart Grids

Accurate battery SoH estimates, derived from ML algorithms and analyses based on large datasets, have significant implications for energy informatics and intelligent systems, such as smart grids. This study explores some of the key applications connecting SoH prediction to improvements in energy efficiency and sustainability.

Energy Informatics and Energy Management in Smart Grids: Energy informatics, the integration of information systems and energy, plays a fundamental role in the efficient management of smart grids. Accurate SoH estimation enables more effective management of second-life batteries by integrating them into storage and distribution networks. This approach not only reduces waste but also enhances the reliability and resilience of electrical grids, especially in contexts involving renewable energy sources [1,10,12].

IoT Devices and Sustainability: SoH prediction models based on DL techniques, such as LSTM and CNN networks, facilitate the preventive maintenance of IoT devices that rely on batteries. These models support a more sustainable economy by optimizing replacement cycles and extending the lifespans of connected smart devices [48,54,64]. The use of these devices in smart grids also reduces reliance on manual interventions, promoting greater automation and efficiency [9,12].

Real-Time Monitoring and Control: Wireless sensor networks (WSNs) integrated with SoH algorithms offer real-time monitoring capabilities, essential for dynamic system adjustments. In smart grids, this enables load balancing and the optimization of the energy distribution, improving the overall system performance [54].

Environmental Impact and Sustainability: The reuse of batteries, underpinned by reliable SoH estimates, contributes to a circular economy by reducing the environmental impact and the carbon footprint associated with the production of new batteries [9,12]. Hybrid models, such as the combination of LSTM with Elman neural networks (ENNs), have already demonstrated accuracy gains of up to 50% compared to classical approaches, increasing confidence in battery reuse for storage systems and smart grids [48].

Through these applications, SoH prediction not only enhances the management and efficiency of smart grids but also reinforces the connections among energy informatics, sustainability, and technological innovation. This highlights the importance of robust prediction methods for the future of intelligent energy systems.

Additionally, it is essential to emphasize that accurate SoH prediction significantly contributes to the evolution of intelligent systems by reducing operational uncertainties and enabling the seamless integration of emerging technologies. The precise forecasting of SoH enhances system reliability by enabling the optimized allocation of energy resources, such as second-life batteries, across diverse use cases. These advancements also support the adoption of predictive maintenance systems, which reduce operational costs while maximizing energy efficiency and long-term sustainability. By converging machine-learning techniques, such as deep neural networks, with advanced data management platforms, SoH becomes a critical metric for decision-making in smart grids and the IoT, driving resilience and sustainability in energy infrastructure.

4. Conclusions

This study highlights the growing importance of ML techniques in estimating the SoHs of batteries, as evidenced by a systematic bibliographic portfolio analysis. The application of ProKnow-C enabled the objective selection of 534 relevant papers from an initial pool of 6032 publications, providing a structured and replicable methodology for characterizing research within this domain.

The results reveal several key trends. First, there has been a significant increase in scientific production in this area, particularly since 2022, with 40% of the selected papers published in 2023. The increasing relevance of battery reuse, driven by the expansion of the electric vehicle market, is expected to further boost research in SoH estimation. Second, the analysis highlights the importance of open datasets, with 60% of the reviewed studies using publicly available data. The NASA Prognostics Center of Excellence repository remains the most cited source, accounting for over half of the open data usage. Overall, the portfolio analysis revealed the presence of 12 available open data sources, with 6 of these sources published in the years 2022 and 2023.

From a methodological perspective, DL techniques, especially LSTM networks and CNNs, dominate the field, with DL accounting for 58% of the implementations. Hybrid approaches, including those combining LSTM and CNNs, are increasingly prominent, representing approximately 25% of the reviewed studies. The emergence of TL in publications since 2022 also highlights a promising avenue for leveraging diverse datasets to address data scarcity and heterogeneity in SoH modeling.

Performance evaluations based on the MIT dataset indicate that classical approaches achieve mean absolute percentage errors of approximately 10%, whereas DL techniques have reduced errors by 50% in some cases. Some studies report prediction errors as low as 1–4% using CNNs, emphasizing the potential of advanced algorithms in this field.

The results presented underscore the critical role of SoH predictions in advancing energy informatics and intelligent energy systems. Accurate SoH estimates enable the integration of second-life batteries into smart grids, enhancing their reliability, supporting renewable energy utilization, and optimizing energy distribution in interconnected systems. Additionally, the application of SoH prediction models in IoT devices and wireless sensor networks facilitates preventive maintenance, reduces waste, and contributes to a circular economy. These methodologies not only transform energy systems by aligning with the goals of efficiency and sustainability but also enhance operational resilience through real-time decision-making processes. This potential extends to the design of smarter, greener infrastructures that meet the evolving demands of global energy markets.

The findings and insights derived from this study, along with prior research conducted by the authors in the field of SoH estimation and energy systems, have contributed significantly to shaping future research directions. The accumulated knowledge from these studies served as a foundation for defining key research gaps, refining methodological approaches, and aligning investigations with emerging challenges in this domain. By integrating lessons learned from previous studies, this review strengthens the proposition of future research strategies and the advancement of machine-learning applications in battery-health prediction [434–439]. Future research could further explore the integration of these methodologies into real-world applications, strengthening their role in smart energy management.

In summary, this study provides a comprehensive characterization of the current stage of the research in battery SoH estimation using artificial intelligence, made possible through the application of a systematic bibliographic portfolio assessment. Notably, no prior review had applied this methodology in this field. These findings contribute to (i) the presentation and exemplification of the use of a systematic methodology for obtaining a bibliographic portfolio, ProKnow-C; (ii) the characterization of the current landscape in the field of SoH estimation using ML; (iii) the presentation of open data sources and their key characteristics, including datasets recently made available, which contribute to the development of new research and comparisons of approaches in this area of development; and (iv) the assessment of performance levels achieved by different researchers in their work, considering the techniques used and modeling conditions applied.

Despite these contributions, this study has limitations. The selection of articles may be subject to bias because of the researchers' prior knowledge and the constraints of ProKnow-C. The integration of generative AI tools with ProKnow-C presents a promising avenue to reduce selection bias by automating and improving the evaluation of titles and abstracts while significantly accelerating the time required to construct a bibliographic portfolio. Furthermore, this study did not conduct a quantitative evaluation of the quality of individual datasets or the specific impacts of variables provided by these datasets. It also lacks an in-depth analysis of the computational performance and predictive power of the surveyed algorithms.

To address these gaps and advance the research in this field, future research directions include:

- Feature-engineering processes with an emphasis on explainability analysis and behavior evaluation across different datasets;
- Implementation of models using the identified open datasets, focusing on assessing the applicability of transfer learning to address datasets with limited volumes;
- Integration of the ProKnow-C methodology with generative AI, aimed at automating the selection process and reducing bias in bibliographic portfolio construction.

Author Contributions: Conceptualization, G.R.S., J.N.M., M.L.M.A., J.P.C., J.A.A., S.F.L. and O.H.A.J.; methodology, G.R.S., J.N.M. and O.H.A.J.; validation, J G.R.S., J.N.M., M.L.M.A., J.P.C., J.A.A., S.F.L. and O.H.A.J.; investigation and simulation, G.R.S., J.N.M. and O.H.A.J.; writing—original draft preparation, G.R.S., J.N.M., J.A.A., S.F.L. and O.H.A.J.; writing—review and editing, G.R.S., J.N.M., M.L.M.A., J.P.C., J.A.A., S.F.L. and O.H.A.J.; project administration, O.H.A.J.; funding acquisition, J.A.A. and S.F.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially supported by the FACEPE agency (Fundação de Amparo a Pesquisa de Pernambuco) throughout a project with references APQ-0616-9.25/21 and APQ-0642-9.25/22. O.H.A.J. were funded by the Brazilian National Council for Scientific and Technological Development (CNPq), grants number 407531/2018-1, 303293/2020-9, 405385/2022-6, 405350/2022-8, and 40666/2022-3, as well as the Program in Energy Systems Engineering (PPGESE) Academic Unit of Cabo de Santo Agostinho (UACSA), Federal Rural University of Pernambuco (UFRPE). G.R.S. was funded by the Federal University of Latin American Integration (UNILA). J.P.C. was supported by a PQ scholarship with the reference number CNPq 305858/2023-8.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

AD	Author Database
AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
ATBLS	Adaptive Time-shifting Broad-Learning System
AUTOML	Auto-Machine Learning
BESS	Battery Energy Storage Systems
BLS	Broad-Learning System
BMA	Bayesian Model Averaging
BMLR	Bootstrap Multiple Linear Regression
BMS	Battery Management System
BNN	Bayesian Neural Network
BP	Bibliography Portfolio
BPNN	Back Propagation Neural Network
CAPSNET	Capsule Neural Network
CC-CV	Constant Current–Constant Voltage
CDTSGANN	Conditional Time Series Generative Adversarial Network
CNN	Convolutional Neural Network
CRNN	Convolutional Recurrent Neural Network
DBN	Deep Belief Network
DBNN	Deep Bayesian Neural Network
DCN	Deep Cross Net
DCNN	Deep Convolutional Neural Network
DELM	Deep Elman Neural Network
DGNN	Deep Gaussian Neural Network
DL	Deep Learning
DNN	Deep Neural Network
DRN	Dilated Residual Network
DSMTNET	Dual Self-Attention Multivariate Time Series Estimation Network
DT	Decision Tree
ELM	Extreme-Learning Machine
ENN	Elman Neural Network
FCNN	Fully Connected Neural Network

FFNN	Feedforward Neural Network
GAM	Generalized Additive Model
GBT	Gradient-Boosting Tree
GNN	Graph Neural Network
GRU	Gated Recurrent Unit
GPR	Gaussian Process Regression
IOWA	Induced Ordered Weighted Averaging
KNN	K-Nearest Neighbors
LCO	Lithium Cobalt Oxide
LFP	Lithium Iron Phosphate
LR	Linear Regression
LSTM	Long Short-Term Memory
MAE	Median Absolute Error
MAPE	Mean Absolute Percentage Error
MLP	Multilayer Perceptron
ML	Machine Learning
NAR	Nonlinear Autoregressive
NARXNN	Nonlinear Autoregressive with Exogenous Input Neural Network
NCA	Lithium Nickel Cobalt Aluminum Oxide
NMC	Lithium Nickel Manganese Cobalt Oxide
PKNN	Prior Knowledge-Based Neural Network
QRF	Quantile Regression Forest
RBFNN	Radial Basis Function Neural Network
RESNET	Residual Network
RF	Random Forest
RMN	Regressive Matching Network
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RPD	Raw Papers Database
RUL	Remaining Useful Life
RVM	Relevance Vector Machine
SoC	State of Charge
SoH	State of Health
SVM/SVR	Support Vector Machine/Regressor
SSEL	Secondary Structural Ensemble Learning
TCN	Temporal Convolution Network
TNN	Transformer Neural Network
TL	Transfer Learning
UNN	Unsupervised Neural Networks
VTN	Vision Transformer Network
PKNN	Prior Knowledge-Based Neural Network
NARXNN	Nonlinear Autoregressive with Exogenous Input Neural Network
DGNN	Deep Gaussian Neural Network

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