Predictive Precision in Battery Recycling: Unveiling Lithium Battery Recycling Potential through Machine Learning

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Abstract

This paper explores the application of machine learning in battery recycling, aiming to enhance sustainability and process efficiency. The research focuses on three key areas: (i) Investigating machine learning's potential in predicting battery recycling viability, optimizing processes, and improving resource recovery. (ii) Assessing machine learning's impact on addressing engineering challenges within recycling. (iii) Introducing a streamlined framework for the application of machine learning in this domain. The study comprehensively analyzes scientific principles, methodologies, and algorithms relevant to battery recycling. Furthermore, it examines practical implications and challenges associated with implementing machine learning techniques in real-world scenarios. Our comparative analysis reveals that the proposed framework offers numerous advantages and effectively addresses common limitations seen in previous models. Notably, this framework provides detailed insights into pre-processing, feature engineering, and evaluation phases, catering to researchers with varying technical skills for effective model application in analysis and product development.

Key words: Lithium battery; Recycling; Machine learning; Data-driven approach; Recycling potential prediction, Recycling LIB

1 Introduction

The recycling of lithium batteries holds significant scientific importance and has a crucial background [1]. With the increasing adoption of lithium batteries in various applications, such as electric vehicles, the need for efficient and scalable recycling processes has become crucial [2][3]. Traditional recycling methods often face challenges related to greenhouse gas emissions, economic viability, and the recovery of valuable materials [4]. Therefore, the utilization of machine learning (ML) in lithium battery recycling has gained attention as a data-driven approach to predict recycling potential. By leveraging real-time, non-invasive measurements and statistical ML , it becomes possible to optimize the recycling process without relying on complex physical models [5]. ML can also contribute to optimizing engineering challenges and improving recycling efficiency [6]. However, further research is necessary to fully explore and harness the potential of ML in enhancing lithium battery recycling.

The application of ML in battery recycling has emerged as a promising avenue due to its potential to address the challenges associated with traditional recycling methods [7]. The growing demand for lithium batteries, especially in the context of electric vehicles and renewable energy storage, necessitates efficient and scalable recycling processes [8]. By utilizing ML algorithms, it becomes possible to predict the recycling potential of batteries, optimize the recycling process, and enhance resource recovery. This data-driven approach offers several advantages, including real-time, non-invasive measurements, and the ability to overcome the limitations of complex physical models.

Moreover, ML can contribute to predicting battery life, optimizing engineering challenges [9], and improving recycling efficiency [10]. By analyzing vast amounts of data, ML algorithms can identify patterns and correlations that are difficult to discern using traditional methods [11]. These algorithms can then generate accurate predictions and insights, enabling more informed decision-making in the recycling industry. For example, previous research has shown the use of support vector regression in predicting the recycling potential for lithium-ion batteries [12]. Recent studies have demonstrated the application of ML in predicting the recycling potential for lithium-ion batteries [13].

This paper aims to explore the motivation and scientific basis behind applying ML techniques in battery recycling, paving the way for more sustainable and effective recycling practices in the future. The objectives of this paper are (1) to investigate the potential of using ML techniques in battery recycling, (2) to assess their impact on enhancing the sustainability and efficiency of the recycling process and (3) proposing a data workflow to guide researchers in using ML techniques in battery recycling. The scope of this research encompasses the scientific principles, methodologies, and algorithms involved in ML for battery recycling. The paper also considers the practical implications and challenges of implementing ML techniques in real-world battery recycling scenarios. By addressing these objectives and exploring the scope, this paper aims to contribute to the advancement of sustainable and effective battery recycling practices by a critical review of the literature, addressing the research gap and proposing a data workflow to the researchers.

This paper begins by exploring the challenges and opportunities surrounding the recycling of lithium batteries. Subsequently, the study focuses on the data gathering approaches and the necessary preprocessing steps for the collected data. Furthermore, it delves into the examination of feature engineering and implementation of ML models for predicting the potential of recycling. This will be followed by presenting model performance and analysis, discussion and providing a framework for facilitating the application of ML models in the field of battery recycling. Lastly, a comprehensive conclusion will be presented. This paper provides significant references for researchers to understand the importance of ML in predicting the recycling potential of lithium batteries, as well as a framework to facilitate the application of ML in this field for both researchers in academia and businesses in industry.

2 Lithium Battery Recycling: Challenges and Opportunities

2.1 Overview of lithium battery components and recycling process

It is crucial to highlight the importance of developing scalable recycling methods for lithium batteries when discussing the various components and recycling processes involved. This becomes even more significant in light of the growing deployment of gigawatt hours of batteries in electric vehicles [14]. Although multiple battery recycling processes are available, their environmental impact in terms of greenhouse gas emissions and economic viability can vary depending on the specific battery chemistry [14]. Therefore, it is imperative for recycling policies to incentivize efficient collection of batteries and encourage the adoption of energetically efficient recycling processes that result in reduced emissions. To provide a comprehensive understanding,

Battery Type	Recycling Process	Advantages	Limitations
Lead-Acid Batteries	Smelting	High recycling efficiency, recovery of valuable lead.	Emissions and pollution control required, potential health risks associated with lead and sulfuric acid exposure.
	Desulfurization	Effective removal of sulfur improves the quality of recovered lead.	Additional steps and processes required, increasing the complexity and cost of recycling.
	Grid Casting	Enables the reuse of lead in battery production, reduces the demand for raw materials.	Requires additional manufacturing processes and energy for casting new battery grids.

Lithium-Ion Batteries	Mechanical Shredding	Facilitates the subsequent separation and recovery of valuable metals.	Requires specialized equipment, and shredding can be energy-intensive.
	Magnetic Separation	Efficient separation based on magnetic properties, aids in the recovery of specific metals.	Limited effectiveness in separating all components, may require additional separation methods.
	Hydrometallurgical Processes	Enables the recovery of valuable metals, reduces reliance on mining.	Requires chemical processes and careful management of waste streams, can be technically complex and expensive.
	Thermal Treatment	Effective recovery of metals at high temperatures can handle a wide range of battery sizes and types.	Energy-intensive process, emissions management and environmental controls needed.
Nickel-Cadmium Batteries	Thermal Treatment	Efficient recovery of valuable metals, reduces cadmium environmental impact.	Requires high-temperature furnaces and careful management of cadmium emissions, limited recycling facilities.
	Hydrometallurgical Processes	Enables the recovery of valuable metals, reduces reliance on primary resources.	Requires chemical processes and waste management, may have lower economic viability due to declining use of nickel-cadmium batteries.
Nickel-Metal Hydride (NiMH) Batteries	Mechanical Shredding	Facilitates subsequent separation and recovery processes.	Requires specialized equipment, and shredding can be energy-intensive.
	Hydrometallurgical Processes	Enables the recovery of valuable metals, reduces reliance on primary resources.	Less developed recycling process compared to other battery types, limited recycling infrastructure, lower economic viability due to declining use of NiMH batteries.
	Thermal Treatment	Effective recovery of metals at high temperatures can handle a wide range of battery sizes and types.	Energy-intensive process, emissions management and environmental controls needed.
Alkaline Batteries	Mechanical Shredding	Facilitates subsequent separation and recovery processes, reduces battery volume.	Requires specialized equipment, and shredding can be energy-intensive.
	Physical Separation Techniques	Enables efficient separation of battery components, enhances the recovery of metals.	May require a combination of multiple separation techniques, additional processing steps and equipment.
	Hydrometallurgical Processes	Enables the recovery of valuable metals, reduces environmental impact.	Requires chemical processes and careful waste management, limited recycling infrastructure, lower demand for recycled materials compared to the production of new batteries.

Table 1- Comparison of Battery Recycling Processes for a range of battery types [15][16][10].

There are various proposed or operational processes for recycling lithium-ion batteries, each with its own set of advantages and disadvantages [17]. While most process routes attain high yields for valuable metals like cobalt, copper, and nickel, the recovery of lithium is limited to a few processes with lower yields, despite its significant economic value. On the other hand, the recovery of other valuable components like graphite, manganese, and electrolyte solvents is technically feasible but poses economic challenges [18]. Processes that utilize a combination of mechanical processing, hydro-metallurgical, and pyrometallurgical steps appear to be effective in obtaining materials suitable for the re-manufacturing of lithium-ion batteries. Conversely, processes that heavily rely on pyrometallurgical steps are sturdy but can only recover metallic components [19].

presents a detailed overview of different battery types, their respective recycling processes, as well as their advantages and limitations.

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2.2 Key challenges in lithium battery recycling

Recycling of lithium-ion batteries (LIBs) is critical given the continued electrification of vehicles and mass generation of spent LIBs. However, industrial- scale recycling is hampered by a variety of factors that make large-scale recycling difficult while maintaining economic viability.

In the last ten years, researchers have shown unwavering dedication to the creation of spent LIB recycling methods that are characterized by high efficiency, low cost, and environmental friendliness. However, the ongoing advancement and substitution of rechargeable batteries present is a challenge because the research for developing recycling processes is not developing with the pace of LIB development process [20]. The rapid pace of LIB development poses a challenge to the advancement of LIB recycling technology because the recycling technology didn't develop with same pace during the time.

Data collection could be a challenge in recycling LIBs. However, it is believed that data collection methodologies, software and hardware are developed for this purpose. Data collection will be discussed later in chapter 3.

The lack of standardization in battery designs and the significant effort needed to convert batteries into metal feedstocks have been major obstacles in the field of lithium-ion recycling [17]. Additionally, the extraction and treatment of emissions generated during the battery recycling process pose another challenge as it necessitates costly infrastructure and advanced equipment [11]. Also, LIBs are designed with a focus on safety and long cell life, which compromises their recyclability. As the cell count increases, the proportion of active and valuable materials relative to the battery weight decreases. Moreover, a higher cell count complicates the opening and separation process, leading to increased recycling costs. [21]. Figure 1 demonstrates the challenges of development of the LIB recycling technology.

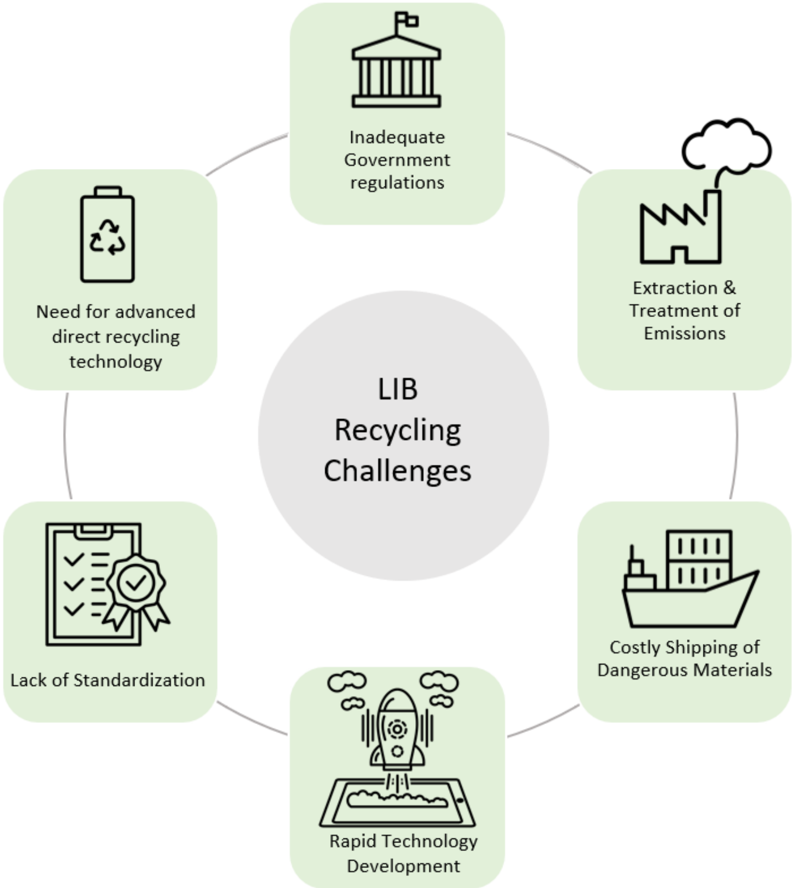

Figure 1- Challenges of LIB recycling technology.

2.3 Opportunities for improving recycling efficiency with ML

The significant metal content found in used LIBs presents a valuable metal source, particularly given the limited global reserves of approximately 62 million tons of lithium and 145 million tons of cobalt. Hence, the recycling of used LIBs is extremely valuable, given the importance of sustainable utilization of these metals [20].

ML presents significant opportunities for enhancing the efficiency of LIB recycling. One such opportunity lies in utilizing ML to facilitate metal leaching from used lithium-ion batteries, enabling swift acquisition of leaching outcomes without the need for extensive and time-consuming experiments [22]. For example, ML assisted robotic systems are developed to overcome the challenge of diverse range of battery packaging during disassembly for recycling [23]. Also, ML can be employed to make precise predictions about battery longevity by using data gathered from charge-discharge cycles during the initial stages of a battery's lifespan [24]. This information can be invaluable in optimizing the recycling process by providing insights into the battery's condition and residual value. Furthermore, ML can be employed to optimize and model engineering challenges encountered in the recycling process, offering a non-invasive and highly accurate solution with minimal processing requirements [25]. By utilizing ML techniques, recycling operations can be streamlined and improved. However, it is important to note that further research is necessary to fully exploit the potential of ML in enhancing the efficiency of LIB recycling. Continued exploration and development of ML applications in this field hold promise for advancing recycling practices and maximizing resource recovery.

Data-driven methods, like ML, can predict LIB recycling potential [26]. By conducting non-invasive, real-time measurements and using statistical techniques, these approaches establish relationships without relying solely on physical models [26]. They help overcome challenges in LIB recycling (section 2.2) and unlock new avenues for enhanced efficiency.

3 Data Collection and Preprocessing Approaches

Data collection and preprocessing are vital for ML models predicting LIB recycling potential. Data collection acquires data from various sources, while preprocessing involves cleaning, converting, and preparing data for analysis. [11]. The quality of the data collected and produced can have a significant impact on the outcomes of any study, making it critical to be meticulous and thorough during this stage [9].

3.1 Sources of data for assessing the recycling potential of lithium batteries

Accurately predicting the recycling potential of lithium batteries requires gathering data from a variety of reliable sources. These sources encompass battery recycling databases, battery manufacturers, environmental agencies, research institutions, industry reports and market research, academic literature, online forums and communities, as well as sensor data and Internet of Things (IoT) devices [10]. Academic research, industry reports, and government publications serve as essential sources of data for assessing the recycling potential of lithium batteries. For instance, research articles by Ciez et al. [27] and Ali et al. [28] offer valuable insights into the subject.

Industry reports provide data on the size of the market and the growth potential of the LIB recycling industry [10]. Government agencies collect and publish data on battery recycling, informing policy decision makers and guiding industry practices. Different data sources have pros and cons. Manufacturers offer accurate details on battery design but may not be publicly accessible. Academic research provides peer-reviewed data on recycling potential but may not be as up-to-date as industry sources. Table 2 presents data sources, applications, and limitations for predicting recycling potential of lithium batteries.

Data Source	Application	Advantages	Limitations
Battery Recycling Databases	Battery recycling databases offer detailed information on recycling rates, processes, and materials recovery, enabling analysis of historical data to identify patterns and trends.	○ Focused and comprehensive information on battery recycling ○ Accurate insights into recycling potential ○ Coverage of emerging recycling technologies and best practices	○ Restricted access or collaboration required for proprietary battery recycling databases ○ Limited data availability to specific regions or battery types ○ Potential impact on generalizability of predictions
Battery Manufacturers	Collaborating with battery manufacturers offers vital data on battery specifications, compositions, and recycling capabilities, facilitating recyclability assessment and improvement opportunities.	○ In-depth knowledge about produced batteries ○ Accurate and detailed data collection ○ Insights into future battery designs and recycling initiatives	○ Reluctance to share proprietary data by manufacturers for competitive reasons ○ Potential bias towards their own products in the provided data ○ Limited representation of the broader landscape of LIB recycling
Environmental Agencies and Research Institutions	Environmental agencies and research institutions provide valuable insights on battery recycling, including infrastructure, regulations, and sustainability, through reports and studies.	○ Rigorous scientific review of data ○ Comprehensive insights into environmental implications of recycling processes ○ Identification of policy and regulatory factors influencing recycling potential	○ Generalized data lacking specific details on recycling processes or battery types ○ Limited scope of studies to certain geographic regions or specific aspects of recycling ○ Potential limitations in granularity and coverage of the data
Industry Reports and Market Research	Industry reports and market research studies provide key insights on the LIB industry, including trends, applications, and recycling practices, informing commercial viability and future demand.	○ Insights into market dynamics, investment opportunities, and technological advancements ○ Holistic view of the market landscape ○ Inform decision-making processes	○ Market reports may not focus exclusively on recycling, and the information provided may be more qualitative or anecdotal. The reports could be biased towards certain market players or may not reflect the most recent developments
Academic Literature	Academic literature enriches scientific understanding of LIB recycling, covering process optimization, recovery rates, and material analysis, providing valuable insights into technical aspects.	○ Peer review and adherence to scientific standards ○ Reliability and validity of data and findings ○ Cutting-edge research and advancements in recycling technologies	○ Academic literature may have a narrower focus on specific research questions rather than practical concerns ○ Some papers may lack readily applicable information for predictive modeling or commercial applications ○ Potential limitations in directly translating academic findings into practical solutions
Online Forums and Communities	Online forums and communities offer insights from experts and enthusiasts, providing real-world experiences, challenges, and solutions for LIB recycling.	○ Knowledge exchange and firsthand experiences ○ Access to diverse perspectives ○ Practical insights complementing formal data sources	○ Lack of standardization and verification in information shared on online forums and communities ○ Challenges in validating the accuracy and reliability of the obtained information ○ Subjectivity of discussions, potentially not representative of the overall industry or recycling practices

Sensor Data and IoT Devices	Sensor data from recycling facilities and IoT devices enables real-time monitoring and optimization of recycling operations, improving efficiency and material recovery rates.	○ Real-time monitoring and control of recycling processes ○ Accurate and up-to-date insights into recycling operation performance ○ Identification of areas for improvement	○ Limited access to sensor data and IoT devices in recycling facilities ○ Challenges in implementing IoT infrastructure and ensuring data privacy and security ○ Requirement for careful preprocessing and interpretation of collected data for use in predictive models

Table 2-Overview of data sources, applications, advantages, and limitations in predictive analysis of LIB recycling potential [10][29][26].

3.2 Data collection methodologies and considerations

Collecting data for LIB recycling potential involves careful methodologies and considerations to ensure the quality and relevance of the dataset [30]. Several factors need to be taken into account during the data collection process. Firstly, it is essential to identify the specific data requirements for predicting recycling potential. This includes determining the necessary variables, such as battery composition, design specifications, recycling techniques used, and recovery rates of valuable metals. Clearly defining these requirements helps in selecting appropriate data sources and designing effective data collection strategies. Secondly, consideration should be given to the representativeness and diversity of the data. It is important to collect data from various battery types, manufacturers, recycling facilities, and geographical locations to capture the broader landscape of LIB recycling. This helps in reducing bias and increasing the generalizability of the predictive models. Thirdly, data privacy and access need to be addressed. While data from battery manufacturers and recycling facilities may provide accurate and detailed information, access to such proprietary data might be restricted due to confidentiality agreements. In such cases, collaboration and partnerships with relevant stakeholders can facilitate data sharing and ensure the availability of essential information.

Furthermore, data quality assurance is crucial. This involves verifying the accuracy, completeness, and reliability of the collected data. Data cleaning techniques, such as removing duplicates, handling missing values, and addressing outliers, should be applied to enhance the overall quality of the dataset [31]. Lastly, the timeliness of the data should be considered. While academic research provides valuable insights, it may not always reflect the most current practices and advancements in the field. Therefore, combining up-to-date data from industry reports, government agencies, and ongoing research projects can provide a more comprehensive understanding of the recycling potential of lithium batteries.

3.3 Preprocessing techniques for cleaning and preparing data

There are specific challenges when LIB recycling data is going to be used for training and testing ML models. One major challenge is the lack of uniformity in battery designs, making it difficult to establish a standardized recycling process [28]. Additionally, the recycling process requires expensive infrastructure and advanced equipment to extract and handle emissions properly [28]. Furthermore, lithium batteries can pose a safety risk if stored alongside regular waste, emphasizing the importance of proper disposal. The growing importance of LIB recycling in the past decade is driven by supply chain limitations for crucial materials like lithium and cobalt, as well as a shift in policies towards greater material circularity to address environmental concerns [28]. As a result, once the data is collected, it needs to undergo preprocessing steps to ensure its suitability for ML analysis.

In fact, data preprocessing is a critical phase in any ML project and involves several techniques such as integration, cleaning, transformation, reduction, and validation [10]. These techniques are employed to enhance the quality and usability of the data for ML algorithms. Figure 2 demonstrates the required preprocessing steps before ML model implementation.

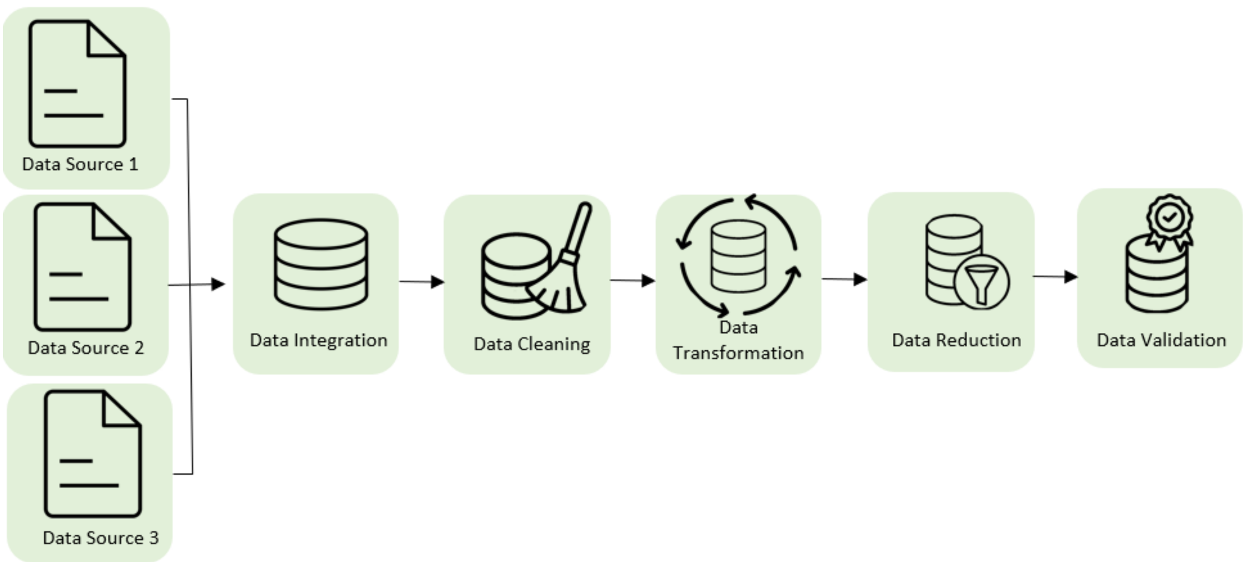

Figure 2-Preprocessing steps before ML implementation.

Data integration is necessary when combining data from multiple sources to create a more comprehensive dataset [32]. This step ensures that all relevant information is included and avoids the loss of valuable data. Data cleaning is the process of eliminating missing values, duplicates, and other inconsistencies that can impact the accuracy of ML algorithms. It involves removing inconsistencies, errors, or noise present in the dataset, addressing missing values, correcting inconsistent entries, and handling outliers [25]. Data transformation involves various operations to prepare the data for analysis. Scaling and normalization ensure that the data is on a comparable scale and follows a desired distribution [25]. Encoding categorical variables allows algorithms to process categorical data effectively [24]. Handling outliers helps in dealing with extreme values that may skew the analysis [25]. Following data integration, cleaning, and transformation, feature reduction techniques can be applied. Feature reduction methods, such as dimensionality reduction or feature selection, are employed to extract the most relevant and informative features for predicting recycling potential [33]. Finally, data validation should be performed to check the accuracy and quality of data before being used for training and testing the ML models [34]. These techniques reduce the computational complexity of the models and mitigate the risk of overfitting. By employing appropriate data collection methodologies and preprocessing techniques, the dataset can be effectively prepared for subsequent steps such as feature engineering and ML model implementation.

4 Feature Engineering for Recycling Potential Prediction

4.1 4.1 Feature engineering

Feature engineering is the process of selecting, transforming, extracting, combining, and manipulating raw data to generate the desired variables for analysis or predictive modeling. It is a crucial step in developing a ML model. The three phases of feature engineering are feature identification, feature extraction, and feature selection [35][36]. Feature identification involves finding relevant variables to predict the target variable. Feature extraction creates new features from existing ones. Feature selection picks the most impactful features for model construction [37]. Figure 3 shows feature engineering steps.

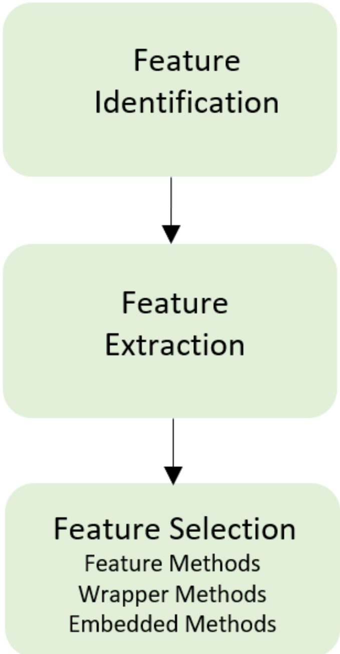

Figure 3- Feature engineering is employed to select high-quality features from the dataset.

4.2 Identification of relevant features for recycling potential prediction

Identification of relevant features is a crucial step in developing a ML model for predicting the recycling potential of lithium batteries. Feature engineering involves selecting and transforming the most pertinent features from raw data to improve model performance. One approach to feature engineering is leveraging domain knowledge to manually identify relevant features. Researchers with expertise in LIB recycling may consider battery chemistry, age, and usage history as significant factors for predicting recycling potential [9]. Alternatively, data-driven methods, like deep learning, can automatically learn relevant features from the data by capturing complex relationships between input data and the target variable [38]. Different opinions exist on identifying relevant features for recycling potential prediction. While some researchers argue for domain knowledge as the best approach, allowing experts to leverage their knowledge, others advocate for data-driven methods that can learn features without prior knowledge. The choice of approach may depend on the specific problem and the availability of high-quality data [38].

4.3 Feature extraction and transformation techniques

Feature extraction and transformation enhance ML models for predicting LIB recycling potential. These techniques involve selecting and transforming the most relevant features from raw data to enhance model performance [38]. Domain knowledge can manually identify and transform relevant features, such as battery chemistry, age, and usage history. For example, researchers knowledgeable in LIB recycling might consider battery chemistry, age, and usage history as essential for predicting recycling potential. Alternatively, deep learning automatically learns complex relationships between input data and the target variable [39]. There are varying opinions on feature extraction and transformation for recycling potential prediction. While some researchers prefer domain knowledge, others argue that data-driven methods are more effective since they can learn relevant features without relying on prior knowledge [38].

4.4 Feature selection methods for improving model performance

In the context of predicting LIB recycling potential with ML , feature engineering can be employed to select high-quality features from the dataset [7]. Feature selection is one of the feature engineering steps that aims to reduce the number of input variables in a predictive model, minimizing computational burden and potentially enhancing performance. It serves several purposes including mitigating overfitting, enhancing model interpretability, and reducing training times [7]. This process is adaptable to different inputs, prioritizing those that have a significant impact on degradation [33]. Handling feature selection in high-dimensional datasets is challenging. Three general approaches are (1) filter methods, (2) wrapper methods, and (3) embedded methods. Usually, a filter method eliminates inadequate features quickly, followed by a wrapper or embedded method.

4.4.1 Filter Methods

Filter methods focus on the general characteristics of the training data to be able to select specific features with independence of any predictor. These methods can be more efficient and computationally less expensive when dealing with high-dimensional data [40]. There are several filter methods which can be applied over different problems. Some of the most popular filter methods include (1) Information Gain, (2) Chi-square Test, (3) Fisher's Score, (4) Correlation confident, (5) Variance Threshold, and (6) Mean Absolute Deviation [41]. Information Gain is an entropy-based method which calculates the reduction in entropy from the transformation of a dataset. This method can be used for feature selection by evaluating the Information gain of each variable in the context of the target variable [42]. Moreover, Chi-square Test can be used for categorical features to test the relation between various features in the dataset and the target variable. In other words, it can be calculated between each feature and the target variable to select the desired number of features with the best Chi-square scores. In order to correctly apply the chi-square test you have to make sure that the variables are categorical and they have been sampled independently. Moreover, the values should have an expected frequency greater than 5 [43]. Furthermore, Fisher's score is another method which can be used to find a feature subset. In a data space spanned by the selected features, this method maximizes the distances between data points in different classes while minimizing the distances between data points in the same class [44]. Correlation Coefficient measures linear relationships between variables, enabling predictions. Good variables highly correlate with the target, but should be uncorrelated with each other [45]. The variance threshold is a simple baseline approach for feature selection. It removes features with low variance or zero variance. Higher variance is considered more informative, but relationships between features or the target are not considered [46]. Mean Absolute Deviation computes the absolute difference from the mean value, without squaring as in variance. It is a scaled measure, where higher Mean Absolute Deviation indicates higher discriminatory power [47].

4.4.2 Wrapper Methods

Wrapper methods search feature subsets, evaluating them with a classifier. They rely on a specific ML algorithm and dataset. A greedy search evaluates subsets against the criterion. Wrapper methods may offer better prediction accuracy than filter methods. Popular ones include Forward Feature Selection, Backward Feature Elimination, Exhaustive Feature Selection, and Recursive Feature Elimination. Forward Feature Selection iteratively adds features, evaluating model performance after each addition [48]. Backward Feature Elimination also follows an iterative approach but it begins with the complete set of features, and then after each iteration features will be removed one-by-one and the accuracy of the prediction will be checked [49]. In addition, Exhaustive Feature Selection is one of the most robust feature selection methods. In this method, the important features and their combination will be ranked through training a ML model with each combination one-by-one. In other words, this method tries every possible combination of the features and returns the best-performing subset [50]. Finally, Recursive Feature Elimination tries to improve the performance of the ML model by removing the least important features, that if you remove them from the dataset, their deletion will have the least effect on training errors [51].

4.4.3 Embedded Methods

Embedded methods combine Filter and Wrapper advantages with reasonable computational costs. They analyze model training iterations to extract influential features. Common Embedded methods are LASSO Regularization and Random Forest Importance. Regularization adds penalties to model parameters to prevent overfitting. LASSO Regularization transforms coefficients, shrinking some to zero and removing corresponding features [52]. Random Forest Importance is a Bagging Algorithm, aggregating decision trees. It ranks features based on how well they improve node purity (reduce impurity). Important features appear early in trees. Pruning below a specific node creates a subset of the most important features [53].

5 ML Models for Recycling Potential Prediction

5.1 Overview of ML algorithms for predicting recycling potential

In the realm of lithium-ion batteries, ML algorithms have proven instrumental in predicting various crucial aspects such as battery health, remaining useful life, and heat generation rate. Researchers have extensively employed several ML algorithms in battery research, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Gaussian Process Regression (GPR), and deep learning algorithms like Recurrent Neural Networks (RNN) and Long Short-Term Memory networks (LSTM)) [12][54].

The selection of the most suitable ML algorithms for recycling prediction in LIB research remains a topic of debate. Cao et al. argued that SVM, ANN, and GPR effectively predict diverse facets of lithium-ion batteries [54]. Conversely, Khumprom et al. contend that deep learning algorithms like RNN and LSTM outperform others due to their ability to capture intricate relationships between input data and the target variable [12]. Ultimately, the optimal approach hinges on the specific problem at hand and the availability of high-quality data. Figure 4 illustrates the fundamental pipeline for developing ML models, beginning with data preparation encompassing data cleaning, training, and learning phases. Subsequently, data prediction, feature extraction, and feature selection come into play. Model training and the utilization of test data follow suit. Finally, prediction constitutes the last stage of the pipeline. However, leveraging the predictions' outcomes as input for the model is essential to enhance accuracy. Ensuring the precise execution of these stages right from the outset holds utmost significance.

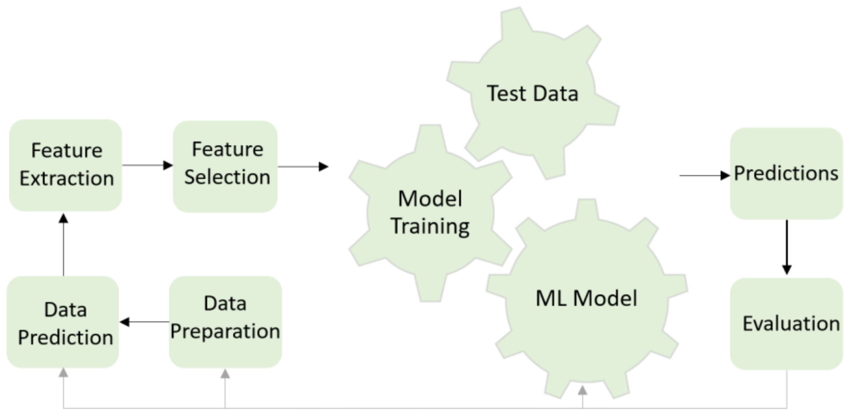

Figure 4- Illustration of the data pipeline, starting from the data preparation stages, progressing to model execution, and concluding with prediction generation. The feedback from predictions is incorporated into both the data preparation and prediction stages.

5.2 Building predictive models using supervised learning techniques

Search shows that relatively no credible research has investigated alternative techniques such as semi-supervised or unsupervised learning for predicting LIB recycling potential. Therefore, this research focuses primarily on the study of supervised learning. In the sphere of LIB recycling potential prediction, supervised learning techniques offer a powerful approach for constructing accurate predictive models. Supervised learning is a branch of ML that entails training a model on a labeled dataset, where the desired output is already known. Subsequently, the trained model can be utilized to make predictions on new, unseen data, enabling insights into recycling potential [55].

Various supervised learning algorithms have proven effective in battery research, contributing to the development of robust predictive models. random forests (RF), decision tree, Support vector machines (SVM), Artificial Neural Networks (ANN), Gaussian Process Regression (GPR), and deep learning algorithms such as Recurrent Neural Networks (RNN) and Long Short-Term Memory networks (LSTM) are among the commonly employed techniques [39]. By training these algorithms on battery recycling-related data, one can harness their potential to generate predictive models specifically tailored to assessing LIB recycling potential. By leveraging supervised learning techniques, researchers and practitioners can unlock the ability to accurately predict the recycling potential of lithium batteries. The utilization of well-established algorithms, coupled with comprehensive and relevant data, empowers the development of sophisticated models that can offer valuable insights for the recycling industry.

5.3 Evaluation metrics for assessing model performance

The evaluation of model performance in predicting LIB recycling potentials poses unique challenges as there is no objective loss function to guide model training or a definitive measure to gauge the quality of the model based solely on loss. Consequently, a combination of qualitative and quantitative techniques has been developed to assess model performance, focusing on the quality and diversity of the generated synthetic data. Quantitative evaluation metrics play a vital role in assessing the performance of generative models. Commonly used metrics include Mode Score, Modified Inception Score (m-IS), Inception Score (IS), Coverage Metric, and Average Log-likelihood. These metrics provide quantitative insights into the quality of the generated data, aiding in the evaluation process [25]. The position of the Evaluation phase that is placed after predictions in the workflow that is demonstrated in Figure 4.

Qualitative evaluation, on the other hand, involves manual inspection of the generated data. While this approach serves as a useful starting point, it is subjective and time-consuming. Nonetheless, combining qualitative and quantitative assessment techniques allows for a more comprehensive and robust evaluation of generative models [25]. The choice of evaluation approach depends on the specific problem at hand and the availability of high-quality data. It is crucial to strike a balance between qualitative and quantitative assessment to effectively evaluate generative models. Table 3 summarizes the metrics for evaluating the performance of ML models in predicting LIB recycling potentials, highlighting their respective advantages and limitations. Leveraging these metrics entails ensuring a robust dataset, employing appropriate model architectures, considering model interpretability techniques, and periodically updating the models to account for evolving dynamics in the LIB recycling domain.

Metric	Description	Pros	Cons
Accuracy	Accuracy measures correctness in ML predictions. In LIB recycling, it reflects the model's ability to make correct predictions by comparing predicted potentials with actual outcomes.	**Improved accuracy**: ML enables accurate predictions by analyzing large datasets and identifying complex patterns. **Efficient data processing**: ML algorithms efficiently process and analyze diverse sources of	**Data availability and quality**: ML models require high quality data for accurate and generalizable predictions. Limited or biased data can impact their effectiveness. **Model interpretability**: Some ML algorithms, like deep neural networks, may lack interpretability. Interpreting predictions is important for trust and transparency in LIB recycling.
Precision and Recall	Precision measures correct positive predictions, while recall measures correct positive outcomes. These metrics evaluate the model's ability to identify recycling potentials and avoid false results.		

F1 Score	The F1 score balances precision and recall, offering a comprehensive performance measure. It is especially valuable in imbalanced datasets with differing positive and negative recycling outcomes.	information for valuable insights. **Automation and scalability:** Trained ML models automate prediction processes, enabling scalability and faster decision making in assessing recycling potentials.	**Model overfitting or underfitting**: ML models can suffer from overfitting or underfitting, affecting their performance. Proper model selection and tuning techniques are crucial to mitigate these issues. **Changing dynamics**: The evolving nature of LIB recycling, including technologies, regulations, and market dynamics, poses challenges for ML models trained on historical data. Adaptability to new scenarios is important.
AUC-ROC	The ROC curve displays the model's performance across thresholds, showing sensitivity against 1-specificity. The area under the curve (AUC) is a single metric indicating overall performance, with higher values reflecting better predictive capabilities.		
mean squared error	The average squared difference between estimated and actual values. It is a measure of the quality of an estimator, and decreases as the error approaches zero.		

Table 3- Metrics, advantages, and limitations of using ML in prediction of LIB recycling potentials [56] [7] [57][58].

6 Model Performance and Analysis: Predicting Lithium Battery Recycling Potential

6.1 Description of the experimental setup and dataset used

Research studies focused on recycling lithium batteries employ diverse experimental setups and datasets tailored to their specific objectives. Typically, these setups involve comprehensive data collection encompassing various aspects of LIB recycling, including battery chemistry, age, usage history, and recycling potential. Data can be sourced from multiple avenues such as laboratory experiments, field studies, and existing databases. Table 2 shows an overview of the data sources and their applications in predictive analysis of LIB recycling potential.

Upon data collection, preprocessing techniques are employed to cleanse, convert, and prepare the data for analysis. Preprocessing methods that are specific to LIB recycling include stabilization, disassembly, and separation processes [59]. These techniques aim to enhance the separation of LIB components and improve the liberation of active electrode materials through mechanical and physical treatments [59].

Diverse perspectives exist regarding the optimal approach for conducting experiments and collecting data in LIB recycling research. Some researchers advocate for laboratory experiments, emphasizing control over experimental conditions and precise measurements. Conversely, others argue for the effectiveness of field studies, which provide realistic data representative of real-world conditions. Ultimately, the choice of approach depends on the specific research problem and the availability of high-quality data [10]. Selecting the most suitable experimental setup and dataset for recycling lithium batteries requires careful consideration as it directly impacts the reliability and applicability of research findings. A comprehensive understanding of research objectives, coupled with the availability of resources and high-quality data, is crucial in determining the optimal approach for experimental setup and dataset selection.

6.2 Performance evaluation of the developed ML models

Performance evaluation plays a vital role in predicting the recycling potential of lithium batteries using ML models. It serves to assess the accuracy, reliability, and areas for improvement within the developed models. As presented in Table 3, multiple metrics can be employed to evaluate the performance of ML models, including accuracy, precision, recall, F1 score, and ROC AUC. These metrics provide insights into the model's ability to correctly classify or predict the recycling potential of lithium batteries [60]. In a data-driven approach, feature engineering techniques are applied to select high-quality features from the dataset. This process enhances model performance by mitigating overfitting and improving interpretability. It is crucial to emphasize that performance evaluation should be an iterative process, adapting to new data and model refinements over time to ensure accuracy and reliability.

6.3 Interpretation and analysis of the results

Interpreting and analyzing the results for recycling lithium batteries involves evaluating the performance of ML models in predicting their recycling potential. This can be achieved by utilizing various evaluation metrics, such as precision, accuracy, recall, and F1 score, to measure the models' performance and compare results against established benchmarks or expected outcomes [60].

Different perspectives exist regarding result interpretation and analysis for recycling lithium batteries. Some researchers argue that using a single evaluation metric, such as accuracy, is sufficient to assess model performance [38]. Conversely, others advocate for multiple evaluation metrics to provide a comprehensive assessment of model performance [60]. The most appropriate approach depends on the specific problem being addressed and the availability of high-quality data.

In addition to evaluating model performance, researchers delve into result analysis to gain insights into the factors influencing the recycling potential of lithium batteries. They may investigate the relative importance of different features in predicting recycling potential or identify patterns and trends within the data. This analysis aids in understanding the underlying mechanisms driving LIB recycling and facilitates the development of effective strategies to improve recycling rates [58] [61]. By employing rigorous interpretation and analysis techniques, researchers extract meaningful knowledge from their results, paving the way for advancements in the field of LIB recycling and the optimization of recycling processes.

7 Discussion

7.1 Comparison of different ML approaches for recycling potential prediction

Several ML approaches have been utilized for predicting the recycling potential of lithium batteries. These approaches can be compared based on their performance, accuracy, and reliability [62]. Common techniques employed in recycling potential prediction include support vector machines, random forests, decision trees, and artificial neural networks [63]. By utilizing these techniques, predictive models can be built to accurately classify or forecast the recycling potential of lithium batteries. The effectiveness of these diverse ML approaches can be evaluated using various metrics such as recall, precision, accuracy, and F1 score [64].

These metrics provide a means to measure the models' ability to correctly classify or predict the recycling potential of lithium batteries. Furthermore, beyond performance comparison, researchers can analyze the results to gain insights into the factors influencing the recycling potential of these batteries. By examining the relative importance of different features in predicting recycling potential or identifying patterns and trends in the data, researchers can inform future studies and develop more effective strategies for improving recycling rates [62] [31].

7.2 Insights gained from the study and implications for battery recycling industry

Studies on ML approaches for predicting the recycling potential of lithium batteries have provided valuable insights for the LIB industry. These insights can help to improve the efficiency and effectiveness of battery recycling processes, and to develop more sustainable strategies for managing end-of-life batteries. One key insight from these studies is the potential for ML to improve the accuracy and reliability of recycling potential predictions. By using advanced ML techniques, such as support vector machines, decision trees, and random forests, researchers have been able to develop predictive models that can accurately classify or predict the recycling potential of lithium batteries [4].

Another important insight is the potential for ML to help identify the factors that influence the recycling potential of lithium batteries. By analyzing the results of ML models, researchers can gain insights into the relative importance of different features in predicting recycling potential. This can help to inform future research and to develop more effective strategies for improving recycling rates. These insights have important implications for the battery recycling industry. By leveraging the power of ML, battery recyclers can improve their processes and develop more sustainable strategies for managing end-of-life batteries. This can help to reduce waste, conserve resources, and protect the environment.

7.3 Limitations and potentials of future research directions

While ML approaches for predicting the recycling potential of lithium batteries offer significant advantages, there are certain limitations that need to be considered in future research. Additionally, exploring potential research directions can further enhance the application of ML in battery recycling. One of the primary limitations is the availability and quality of data. ML models require large amounts of high-quality data to train effectively. The availability and quality of data on the recycling potential of lithium batteries may be limited, which could impact the performance of ML models [37]. To address this, comprehensive experimental data is needed to accurately learn the long-term degradation characteristics of batteries over multiple cycles and hours of operation [65].

Another limitation is the complexity of ML models. These models can be intricate and challenging to interpret, making it difficult to understand how they make predictions and identify potential sources of error [25]. Overcoming this challenge requires developing techniques to enhance model interpretability, enabling researchers to gain insights into the decision-making process of ML models. Despite these limitations, there are several promising future research directions that can overcome these challenges and further advance ML in the field of battery recycling:

1- **Technical Aspects**: Research can focus on leveraging ML to optimize the safe and efficient automatic disassembly of retired lithium-ion batteries (LIBs) [23]. Analyzing battery designs and structures using ML algorithms can optimize disassembly processes, ensuring both safety and efficiency. Additionally, ML can aid in the development of alternative rechargeable batteries and resource management for LIBs, facilitating the efficient recovery of multiple components [66].

2- **Economic Aspects**: Future research can explore how ML algorithms can optimize recycling processes to reduce costs and increase the value of recycled products. By analyzing cost-benefit calculations, ML can identify strategies to achieve economic efficiency, such as implementing simplified processing techniques and producing high-value-added or high-purity recycled materials. Furthermore, ML can help in analyzing and mitigating concerns related to secondary pollution, optimizing waste treatment processes, and maximizing overall recycling benefits [66].

3- **Environmental and Safety Aspects**: Research efforts can focus on leveraging ML to enhance the energy efficiency of battery manufacturing processes. By identifying areas for optimization, ML can contribute to reducing the environmental impact of rechargeable batteries. Additionally, ML can aid in the selection of environmentally friendly materials, such as binders and electrolytes. It can also assist in developing sound control measures and prevention equipment to minimize potential risks of secondary pollution during the recycling process [66].

4- **Data Collection**: Future research can explore the potential of ML algorithms in establishing comprehensive management platforms for battery recycling traceability. Through the collection and analysis of data across the entire life cycle of batteries, from production to retirement and recycling, ML can enable real-time monitoring, facilitate evaluation of recycling technologies, and support the assessment of retired batteries for secondary use [66].

8 Proposed framework for using ML in predicting lithium battery recycling potential

Addressing the discussed limitations and exploring the mentioned potential research directions will unlock the full potential of ML in LIB research and recycling. By doing so, the industry can achieve greater efficiency, reduce waste, conserve resources, and foster a more sustainable approach to managing end-of-life batteries. Collaboration between academia, industry, and policymakers will be crucial in advancing these research directions and realizing the benefits of ML in the battery recycling industry. Hence, this research proposes a framework for using ML in predicting LIB recycling potential. Figure 5 demonstrates the high-level framework that is proposed in this research. There are several major phases in the framework which are described below.

1. **Data Retrieval**: The dataset should be collected from a range of resources that are explained in detail in section 3.
2. **Data Preparation:** This phase is mainly data processing steps such as data cleaning, data visualization and data wrangling.
3. **Feature Engineering**: This is the process of selecting, transforming, extracting, combining, and manipulating raw data to generate the desired variables for analysis and predictive modeling. The four phases of feature engineering in this framework include (1) feature identification, (2) feature extraction, and (3) feature transformation, and (4) feature selection which are explained in detail in section 4 and the relevant workflow is presented in Figure 3.
4. **ML Model Development**: In the model development process, data features should be fed into a ML algorithm to train the model. The objective is usually to optimize a specific cost function, aiming to minimize errors and generalize the representations derived from the data. ML modelling is described in detail in section 5.
5. **Model Optimization**: Models consist of different parameters that should be adjusted during a process known as hyperparameter tuning. This optimization aims to obtain models that deliver the best and most optimal outcomes. This process is described in detail in section
6. **Model Evaluation:** After constructing models, they should be assessed and tested using validation datasets. Performance evaluation should be conducted based on metrics such as accuracy, F1 score, recall, precision and others. Model evaluation is described in detail in section 6. Additionally, the feature engineering process can be iterated to enhance the performance of the evaluated model.
7. **Model Deployment**: Chosen models should be implemented in production and undergo continuous monitoring based on their predictions and outcomes.

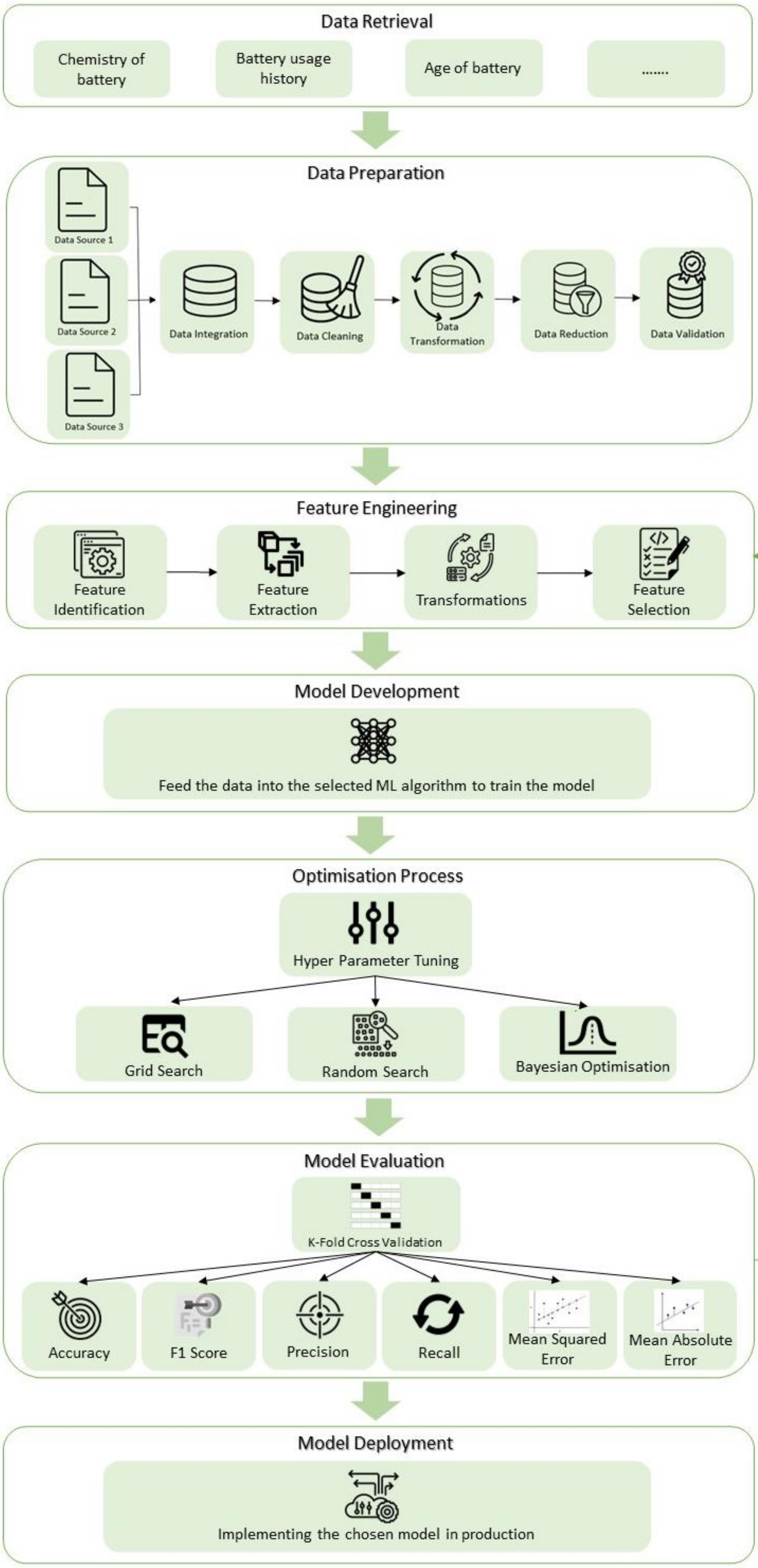

Figure 5- High-level framework of the proposed ML pipeline with the major phases for lithium battery recycling.

Table *4* provides a comprehensive comparison of information pertaining to data-oriented and intelligent methodologies within the realm of LIB technology. Specifically, it showcases various frameworks within battery technology, systematically detailing their scopes, advantages, and limitations, aiming to illuminate the diverse array of prevalent methodologies employed in battery recycling technology. By comparing these exemplary frameworks against our innovative approach and framework (Figure 5), the table serves as an essential reference, offering vital context to underscore the unique nature and potential of our tailored framework within the realm of battery recycling. This deliberate comparison effectively highlights the distinctive strengths and contributions of our proposed methodology, positioning it within the broader spectrum of existing battery technology methodologies.

Research shows the absence of an established framework for the application of ML in LIB recycling. Consequently,

Table *4* is designed to present frameworks from similar fields to address this gap and provide valuable insights. The table presents a comparative analysis between the conceptual framework depicted in Figure 5 in its second row and similar frameworks employed in ML applications within LIB research in rest of the rows. The table underscores the distinctive novelty of the proposed framework, specifically emphasizing its innovation in the application of ML techniques to the recycling of LIBs.

Frame work	**Example**	**Scope**	**Advantages**	**Limitations**

Lithium battery recycling (Figure 5)	**High-level framework of a ML pipeline with the major phases for LIB**	○ Offering a more sustainable approach to managing end-of-life LIBs using ML. ○ Developing scalable LIB recycling methods. ○ Unlocking the full potential of using ML in LIB recycling. ○ Achieving greater efficiency, reducing waste, and conserving resources in LIB recycling.	○ Ability to continuously learn and adapt to emerging technologies. ○ A sustainable approach which is not limited to specific ML or deep learning models. ○ Provides a clear structure for pre-processing. ○ Emphasizes on feature engineering phase that can boost the performance of the models dealing with complex features. ○ Suggests a more robust evaluation approach which improves the reliability of the prediction. ○ Considering different hyper parameter tuning techniques to find the optimum values which significantly impacts the performance of the models. ○ The clear structure for pre-processing, feature engineering, and evaluation phases, can help the researchers with low or moderate technical skills to benefit from applying ML models in their analysis and product development.	○ Significant computational resources might be required based on the selected algorithm. ○ Obtaining large amount of high-quality data related to LIB recycling can be costly.
Reliability of LIB [67]	Framework of the digital twin for the reliability of LIBs	○ Digital Twin creates a model to predict LIB life & assess LIB reliability. ○ Stochastic Model considers randomness & dispersion in LIB degradation. ○ Uses Bayesian algorithms to refine predictions over time. ○ Plans maintenance based on accurate RUL predictions.	○ Using digital twin for precise LIB behavior prediction. ○ Real-time monitoring provides continuous assessment by mapping physical LIB to digital models. ○ Considerate modelling accounts for randomness, enhancing predictive capability. ○ Improves accuracy with evolving Bayesian-based models.	○ Dependents on sensor & historical data availability. ○ Requires significant computational resources & expertise. ○ Model simplifications might not capture all real-world complexities. ○ Validation through experiments, may not apply universally.
Predictive maintenance [68]	Framework for the predictive maintenance of LIBs	○ Development of predictive maintenance strategies for LIB using real-time monitoring & data analysis. ○ Utilizing ML models to predict LIB SOH & RUL based on the NASA battery dataset. ○ Analysis of crucial battery features during charging & discharging for SOH determination & RUL prediction.	○ Cost-effective equipment management. ○ Accurate battery SOH & RUL predictions. ○ Methodology, including feature selection & predictive analysis. ○ Comprehensive NASA battery dataset for in-depth analysis & modeling.	○ Limited data from only four batteries with 170 cycles may limit generalization. ○ The limited choice of ML models could impact prediction accuracy. ○ Variations in conditions not fully covered may affect predictive accuracy. ○ Definition & determination of RUL might need standardization for industry use.
Materials development & state prediction [57]	Flowchart of the " ML-Molecular dynamics" ionic conductor screening process	○ Finding new battery materials by forecasting their properties. ○ Estimating battery states (SOC, SOH, & RUL). ○ Developing intelligent BMS for accurate battery behavior prediction. ○ Electrode & electrolyte material properties prediction. ○ Evaluating battery performance & predicting safety-related incidents.	○ Fast screening of vast datasets. ○ Accurate predictions, aiding better decision-making. ○ Intricate property relationships, offering insights beyond traditional methods. ○ ML models help precisely estimate battery behavior, crucial for usage optimization.	○ Obtaining large, quality training data for ML models, especially for rare events, can be costly. ○ Reliability of models hinges on quality & representativeness of training data. ○ Safety risks & cost implications in battery design can restrict real-world applications of ML.
SOH & RUL estimation [69]	Framework to estimate SOH & RUL	○ Deep learning prognostics framework for SOH & RUL estimation of LIB. ○ Applied to charge curve using the same protocol employed during degradation experiments to confirm its feasibility with respect to actual applications.	○ Using parameter optimization at two stages of data training ○ Definition of 3 different phases inside the framework	○ Application limited to using deep learning for SOH & RUL estimation. ○ The framework is not working efficient with low number of data because it is using deep learning. ○ Understanding the rationale and mechanisms of the process becomes challenging due to the utilization of deep learning layers.

Table 4-Comparison of data-oriented and smart approaches in battery technology: frameworks, scopes, advantages, and limitations. RUL and SOH stand for Remaining useful Life and State of Health respectively.

9 Novelty and Knowledge Contribution

This study not only explores Machine Learning algorithms for battery recycling prediction but also conducts an in-depth analysis of their practical impact on engineering challenges within recycling processes. The outcomes can help researchers and businesses by providing useful insights and a clear understanding of the current state of ML applications in LIB recycling and the relevant challenges. Additionally, a framework has been proposed in this study, offering a more sustainable, scalable, and tailored approach to managing end-of-life LIBs using ML. By unlocking the full potential of using ML in LIB recycling, this framework can address the identified challenges in this field and help with achieving greater efficiency, reducing waste, and conserving resources in LIB recycling.

The proposed framework in this study has also been compared to other existing frameworks which were previously used, and the results show that this framework can provide more advantages and can address the most common limitations that previous frameworks were facing with. According to table 4, it was realized that one of the most common and serious limitations in the previous frameworks was their limitation to particular ML models. In contrast to alternative frameworks, our framework is not limited to specific ML models, and it can be used for developing variety of ML and deep learning models. Furthermore, our framework provides more details on the pre-processing, feature engineering, and evaluation phases, that can enable the researchers with low technical skills to apply ML models in their analysis and product development. More precisely, emphasizing on feature engineering steps in this framework, which was not seriously considered in previous frameworks, can significantly impact the performance of the models. The outcomes of comparing this framework with previous frameworks can clarify the practicality and efficiency of this framework in different scenarios.

10 Conclusion

The importance of recycling lithium batteries cannot be overstated, especially with the growing prevalence of lithium batteries in various applications, such as electric vehicles. However, traditional recycling methods face significant challenges in terms of greenhouse gas emissions, economic viability, and the recovery of valuable materials. To address these challenges, there is a pressing need to develop efficient and scalable recycling processes for lithium batteries.

This study has demonstrated the significance of incorporating ML into the development of scalable recycling methods, particularly in the context of the increasing demand for electric vehicles. By emphasizing the importance of recycling policies that encourage efficient battery collection and the adoption of energetically efficient recycling processes to reduce emissions, the potential for positive impact becomes evident. Furthermore, the paper has provided a comprehensive overview of different battery types and their recycling processes, offering valuable insights into the advantages and limitations of each approach.

A notable contribution of this research is the exploration of the opportunities presented by ML in enhancing the efficiency of LIB recycling. The application of ML for metal leaching from used lithium-ion batteries has shown promise, streamlining the acquisition of leaching outcomes without extensive and time-consuming experiments. In the process of developing ML models for predicting recycling potential, the critical phases of data collection and preprocessing have been thoroughly examined. Various data sources and methodologies have been discussed, highlighting the need for meticulousness and thoroughness during this stage. Additionally, the paper has explored feature engineering, which involves selecting, transforming, and extracting relevant features from raw data to improve model performance.

Among the ML algorithms investigated, including Artificial Neural Networks, Support Vector Machines, Gaussian Process Regression, and deep learning algorithms like Recurrent Neural Networks and Long Short-Term Memory networks, have been used for predicting recycling potential. The performance evaluation of these models, utilizing metrics such as accuracy, precision, recall, F1 score, and ROC AUC, is a critical step to assess accuracy, reliability, and identify areas for improvement.

While ML holds promise for recycling potential prediction, this research also acknowledges certain limitations and proposes potential research directions to address these challenges. By overcoming these limitations and exploring new research directions, the full potential of ML in LIB recycling can be realized. A significant contribution of this study is the presentation of a framework that facilitates the application of ML in LIB recycling. This framework serves as a valuable guide for researchers and practitioners looking to integrate ML into this field effectively. This framework was compared with other existing frameworks and the outcomes show that it can provide more advantages and can address most common limitations that the previous frameworks were facing with. By providing more details on the pre-processing, feature engineering, and evaluation phases, this framework can also enable the researchers with low technical skills to apply ML models in their analysis and product development.

Authorship contribution statement

Conceptualization, A.V.; Data curation, A.V. and Y.G.; Formal analysis, A.V. and M.H.A.; Investigation, A.V. and M.H.A.; Methodology, A.V. and Y.G. and M.H.A; Project administration, A.V. Validation, A.V. and M.H.A.; Visualization, A.V. and M.H.A.; Writing—original draft, A.V.; Writing—review and editing, A.V. and Y.G. and M.H.A. All authors have read and agreed to the published version of the manuscript.

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Conflicts of interest

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