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Digital Twins for Lithium-Ion Battery Health Monitoring with Linked Clustering Model using VGG 16 for Enhanced Security Levels

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Abstract— Digital Twin (DT) has only been widely used since the early 2000s. The concept of DT refers to the act of creating a computerized replica of a physical item or physical process. There is the physical world, the cyber world, a bridge between them, and a portal from the cyber world to the physical world. The goal of DT is to create an accurate digital replica of a previously existent physical object by combining AI, IoT, deep learning, and data analytics. Using the virtual copy in real time, DTs attempt to describe the actions of the physical object. Battery based DT's viability as a solution to the industry's growing problems of degradation evaluation, usage optimization, manufacturing irregularities, and possible second-life applications, among others, are of fundamental importance. Through the integration of real-time checking and DT elaboration, data can be collected that could be used to determine which sensors/data used in a batteries to analyze their performance. This research proposes a Linked Clustering Model using VGG 16 for Lithium-ion batteries health condition monitoring (LCM-VGG-Li-ion-BHM). This work explored the use of deep learning to extract battery information by selecting the most important features gathered from the sensors. Data from a digital twin analyzed using deep learning allowed us to anticipate both typical and abnormal conditions, as well as those that required closer attention. The proposed model when contrasted with the existing models performs better in health condition monitoring.
Keywords— Digital Twin, Lithium-ion Battery, Deep Learning , Battery Life, Health Condition, VGG 16, Device Security.

I. INTRODUCTION

Mobile phones, laptops, energy storage systems, military gadgets, aircraft, etc. all benefit from using lithium-ion batteries as an alternative energy source [1]. As industrial technology develops at a quick pace and the level of product integration and intellectual capacity continues to rise, the use cases for lithium-ion batteries that become increasingly intricate [2]. Predictive maintenance is an effective method for increasing system reliability, reducing downtime, and elongating the useful life of lithium batteries [3]. Predictive maintenance relies heavily on information about the battery's health, therefore reliable methods of estimating the battery's remaining life span and identifying any difficulties it may be experiencing are crucial [4].

Predicting battery life and gauging reliability are two of the biggest challenges for designing uses of lithium-ion batteries [5]. The basic categories of existing methods are data-based, model-based, and data-model fusion. Multiple researchers, employing a modified long short-term memory (LSTM) neural network (NN) technique [6], created a prognostic framework for multiple batteries to better measure health state and anticipate battery life. Current lithium-ion battery life expectancy estimates are largely based on historical data and models, which may not be sufficient for exact preventative maintenance [7]. Beyond basic prior knowledge, a mix of real-time and historical data could improve the current state of life prediction.

Because of developments in sensor technology as well as information processing techniques, the concept of the digital twin provides ideas for and practical means to address these concerns. Digital twins, which incorporate digital technology and a simulated version of model technological advances to explore and anticipate the state of operation of physical space [8], provide an important basis for theory and technical assistance for the link and instantaneous relationship between virtual and physical space. Connecting the digital twin with requirements for product reliability takes advantage of its primary benefit, the exact and real-time mapping among virtual and physical space [9]. The figure 1 illustrates the parts of a Lithium-ion battery.

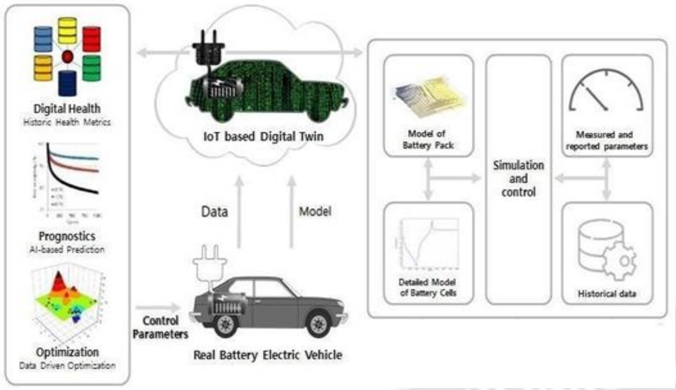

Fig 1: Components of Lithium-ion Battery

A lithium-ion battery is a complex system due to its nonlinear and interconnecting internal features and the fact that its life is dependent on so many external factors. Significant challenges exist in the areas of accurate state estimation, quick charging, temperature control, and extending service life [10]. To determine DT, sensors measure the battery's voltage, current, temperature, etc., and this data is utilized to construct a structural model, an ageing approach, a thermal model, etc., in the virtual world [11]. Data monitoring, state estimation, health estimation, controlling the temperature, and other functions spanning the battery's entire life cycle can all be attained in real time with the help of AI, as can feedback control of the physical battery and simultaneous updates to the virtual model. The ability to visualize data from the battery is another way in which Battery DT improves battery transparency [12] and readability [13]. The development of digital and smart battery management systems can also be guided by this. The use of DT to manage complicated systems and a DT framework for battery infrastructure is depicted in Figure 2.

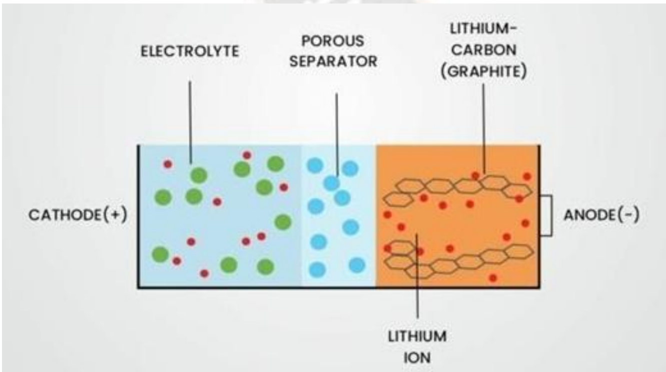

Fig 2: DT in Battery Management System

The standard definition of DT is a model that, given enough input data, can faithfully simulate the behavior of a real-world system [14]. This DT emphasizes the relevance and completeness of the statement's attempt to reproduce the behavior. Though DTs may at first glance appear to be carbon copies, it may not be able to replicate every aspect of human conduct exactly. For example, in battery DTs it is not required to digitally replicate the molecular, liquid [15], and structural actions of every cell component. DTs need not attempt a 1:1 system replication. As a result, the feasibility of a full high-fidelity DT [16] that faithfully replicates the entire physical system and efficiently optimizes services while requiring as little in the way of resources as possible is still a work in progress[17]. The constraints on the precision of the model, the expenseof the implementation, and the difficulty of the task will vary from one use case to the next [18]. Even less is known about DTs and how they develop during a person's lifetime [19]. Boththe number of DTs required throughout a given lifespan nor thetransitions and links that exist between DT's software components have been the subject of extensive study.

Current lithium-ion battery life expectancy estimates are largely based on historical data and modeling [20], which may not be sufficient for exact preventative maintenance. Beyond basic prior knowledge, the combination of real-time and historical data could improve the current state of life prediction. As developments in sensor technology along with data analysis methods grow, the idea of the digital twin offers concepts and instruments for tackling the aforementioned difficulties [21].

Digital twins combine cutting-edge digital technology and virtual simulation of model technology to investigate and predict the operating condition of physical space in real time [22]. Connection with product reliability requirements is a natural useof the digital twin's core benefit of real-time and exact relationship between virtual and real space [23]. The technology of digital twins has been used to analyze and anticipate product performance decline, failure, and lifetime [24]. In order to trackhow well Lithium-ion batteries are doing, this research suggestsa Linked Clustering Model trained on VGG 16. In this study, deep learning is used to extract battery statistics by choosing themost relevant sensor data features.

II. LITERATURE SURVEY

The concept of a DT has recently grown in favour among engineers due to the fact that it makes it easier to integrate physical and virtual components over a building's entire lifecycle. Machine learning (ML), 5G/6G, cloud computing, and the Internet of Things are only some of the enabling technologies that have accelerated the translation of DT from theory to practice. Dang et al. [1] proposed a DT framework for structural health monitoring that makes use of cloud computing and deep learning to perform real-time monitoring and preventative maintenance. The mathematical, finite-element, and machine learning submodels, along with the structural partsand device measurements, make up the framework. With the help of a cloud-based infrastructure and a user-friendly web app, the authors can enhance the flow of information between the actual building, the digital model, and the people working

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on it. The feasibility of the proposed framework is demonstrated by case studies demonstrating the identification of damage to bothmodel and real bridge structures using DL algorithms, with an accuracy of 92%.

Due to their widespread use in a broad variety of electronics and the relatively high safety and reliability criteria in practice, researchers have delved deeply into the problem of estimating the state of health (SOH) of Lithium-ion batteries, which is directly related to the degradation of performance. For maximal capacity to be observed, a full charge/discharge cycle must be completed, as this is the case with end-of-cycle estimation, which is employed in the conventional SOH estimation methodology with digital twin. However, under dynamic operating conditions, partially discharged data cannot be used toreliably estimate SOH for Lithium-ion batteries in real time. Qin et al. [2] proposed a digital twin infrastructure for continuous SOH monitoring and model updates for batteries to address this information gap. There are three primary parts to the digital twinsystem proposed for SOH estimation in real time without a fulldischarge. To begin dealing with the variable training cycling data, the author first provided energy discrepancy-aware cycling synchronization, which aligns cycling data while ensuring the same data structure. Second, the degradation behavior across cycles is encoded into a time-attention SOH estimation model,which is then used to eliminate the impact of small sample sizes. As a result, the author examined the relevance of different training sample intervals over time. In order to provide real-time SOH estimation that is not dependent on a full discharge cycle,a data reconstruction method based on similarity analysis has been presented for online deployment.

There has been a resurgence of interest in bringing Emotion Recognition (ER) to the healthcare sector as a result of recent advancements in ML and DL. The ER system needs to be combined with a real-time digital twin of the human in order to monitor, comprehend, and improve the physical entity's capabilities, and to provide constant input to improve quality of life and well-being for personalized healthcare. Some of the technical hurdles that must be traversed while creating such ER systems in real time include limited datasets, occlusion and lighting difficulties, discovering meaningful features, incorrect emotion categorization, and high implementation costs. To solve this issue, Subramanian et al. [3] designed a user-friendly, efficient, and adaptable ER system based on a webcam. In addition, the author provided a holistic architecture that combines an ER system with a digital twin setup, which facilitates the evaluation of the anticipated outcome prior to administering the most effective customized healthcare treatment, ideally before the onset of a potentially deadly condition. The proposed ER system had much shorter training times without reducing accuracy, yielding promising outcomes. Patient conditions may be monitored in real time, potentially fatal diseases can be identified early, and the most cutting-edge, effective therapies can be made available to hospitals.

The intention of the suggested model is to fix the vulnerabilities of DTs in a CITS by employing a DL environment. The DL process has been modified; Convolutional Neural Network (CNN) and Support Vector Regression (SVR) have been implemented; and DTs technology has been added. Finally, a CNN-SVR based CITS DTs model is developed, and simulation experiments are used to analyze its effect on security. Lv et al.[4] proposed a method that improves upon state-of-the-art security prediction methods by producing results with an accuracy of 90.43 percent. More so, in terms of Precision, Recall, and F1, the proposed method outperforms preexisting methods. The data transmission efficiency of the proposed method is compared to that of other algorithms currently in use. The proposed method ensures that critical messages will be responded to in less than 1.8 seconds. However, it improves upon previous attempts at this task, maintaining high data transfer rates and providing drivers with optimal route planning despite varying road conditions. The transportation system's vulnerability to these factors is further examined. When the path guidance strategy is made more transparent, market penetration, following rate, and congestion are improved. Using the proposed DL algorithm model as an experimental starting point, researchers can work to improve urban transportation in ways that minimize data transmission delay, increase forecast accuracy, and fairly change routes to slow the spread of traffic jams.

Smart structural health monitoring (SHM) for large-scale infrastructure is gaining traction in the engineering community as a result of its many advantages, such as early damage detection, the best maintenance plan, and low resource consumption. Despite its allure, this is a challenging problem Since it requires the continuous processing of information from a massive number of sensors, all of which are imperfect due to noise. Therefore, Dang et al. [5] developed an end-to-end framework that uses the inherent physical features of raw data with a sophisticated hybrid deep learning model (1-DCNN- LSTM) made up of the CNN and the LSTM algorithms. Empirical mode decomposition, the discrete wavelet transform, and the autoregressive model are just a few of the signal processing techniques that are combined in this approach. The 1-DCNN-LSTM hybrid deep learning network draws on the strengths of both CNN and LSTM networks. The proposed method is as accurate as the powerful 2-D CNN in damage detection, and it is suitable for real-time SHM due to its lower time and memory complexity, as demonstrated across three case studies utilising both real and synthetic data sets.

These days, sensors allow us to keep tabs on ships in real time. The importance of ship intelligence has been brought to the forefront by the easy availability of data. As ship intelligence has progressed, so has the desire to use cutting-edge data-driven solutions for optimizing operations. Ship motion data, which reflects the relationship positioning performance of the vessels, can be used to detect and isolate drift-offs caused by failed thrusters. Thruster failure detection and localization is framed as a time-series classification problem. A CNN is used by Han et al. [6] to learn the mapping between the motion sequence recorded and the present state of the thruster. CNN must first generate task-specific properties before it can identify raw data from time series sensors. The information used in this analysis was generated by the Offshore Simulation Centre AS's high- quality simulator. Experiments have proven that the proposed strategy is 95% effective in identifying and isolating malfunctioning thrusters.

By facilitating the integration of more renewable power generation, improving the grid, and creating more flexible energy systems, lithium-ion batteries (LIB) play a critical role in the transition to a world with zero net carbon emissions. However, their short useful life and high price prevent broad adoption of battery technologies like renewable resource storage. The usable life of a battery is very sensitive to the materials structure, system design, and operating conditions, adding another layer of complexity to the challenge of controlling and managing battery systems. With digitalization and AI working together, battery management system awareness may be greatly increased, and battery storage units' performance can be optimized. Determine the battery's health, maintenance requirements, and expected lifespan with an accurate estimation of its state of charge (SOC). Zhao et al. [7] presented a digital twin-driven framework for SOC estimation in a li-ion battery by combining a LSTM with an extended Kalman filter (EKF) model. LSTM provides EKF with more accurate initial SOC estimates and impedance model data.

Traditional efforts to study alternative energy vehicles have focused on lithium-ion batteries, despite the fact that their internal reactions are complex and that fundamental questions about things like battery ageing and safety remain unanswered. Due to its study and preliminary application in complex systems like aerospace, the digital twin can be used to overcome the existing bottleneck in battery research. Wang et al. [8] organized the evolution, fundamental ideas, and fundamental components of the digital twin, and it provides an overview of current research approaches and problems in battery modelling, state estimation, remaining useable life forecast, battery safety, and control. The author also described the digital modelling, real- time status estimation, dynamic charging control, dynamic temperature management, and dynamic equalisation control methods used in an intelligent battery management system. The future of digital twin development in the field of batteries is also outlined. Finally, the author reviewed the history and potential of smart battery management in a quick summary.

It is vital to precisely anticipate the lifespan of lithium-ion batteries and evaluate their reliability for preventative maintenance purposes. It has always been difficult to accurately describe the dynamic and stochastic features of a battery's life. To guarantee the dependability of lithium-ion batteries, Yang et al. [9] described the concept of a digital twin and proposed employing one to estimate how many more cycles they will live for. The capacity degradation model, the stochastic degradation model, the life prediction model, and the reliability evaluation model are all created to define the unpredictable nature of battery degradation and the variation in the lifespan of multiple cells. An adaptive evolution strategy is given for the digital twin model to improve prediction accuracy, and is then verified experimentally. Finally, battery life prediction, reliability assessment, and predictive maintenance built on the foundation of digital twins are put into practice. The results validate the reliability digital twin across its whole service life. The error rate can be brought down to less than 5% by using the adaptive evolution technique.

There can be no gains in battery system security, dependability, or efficiency without first addressing the issue of battery management. Weihan et al. [10] developed a cloud-based battery management system to improve battery systems' processing speed and data storage capacity. IoT enables the construction of a digital twin for the battery system through the collection and transmission of data about batteries to the cloud, where it can be examined by battery diagnostic algorithms to offer insights about the charge and age of the batteries. Cloud-optimized methods for estimating the battery's state of charge and health are created, and the usage of similar circuit models in the digital twin for battery systems is explored. The adaptive extended H-infinity filter can be used to estimate the level of charge of lithium-ion and lead-acid batteries even if there is a significant error in the initialization. In addition, the battery's capacity and power are monitored via an innovative state-of-health estimate algorithm based on particle swarm optimization.The functionality and stability of the cloud battery management system for both stationary and mobile applications are verified by field and experimental testing of prototypes.

III. PROPOSED METHOD

DT technology makes use of a plethora of sensors to obtain real-time measurements of the properties of physical entities, allowing for the establishment of a digital model in a simulated environment and the realization of dynamic simulation of the system. Data from dynamic simulations are analyzed using the AI algorithm to monitor the shifting patterns of underlying physical events [25]. With digital twin technology, not only can the technical state of high voltage electrical equipment be more accurately identified, but hidden links among various variables can be established, and new practical information may be gleaned through the use of Big Data analysis and machine learning techniques [26]. Even while battery research has gotten more thorough and refined in recent years, there are still many questions that need answers. Systems for battery management and battery balance management rely on an accurate assessment of the battery's present status to prevent overcharging and over discharging of a Li-ion battery [27]. The internal interactions of lithium-ion batteries are largely non-linear and tightly coupled, making for a challenging description. This indicates that DT could be used to address battery management difficulties at the state level [28].

Big data refers to extremely large datasets that are difficult to manage with traditional database management systems. Big data systems should have the capabilities of integrating data, protecting data, managing data, analyzing data in real time, visualizing data, and keeping data private [29]. Twin data combines sensor data, model data, and data that has been combined virtually or in practice. Big data can sort through the mounds of data created by the DT to better characterize and forecast the consequences and processes of real occurrences. The DT model and big data are compatible with one another in terms of the data kinds and other metrics used. Between the realm of massive data in cyberspace and the world of particles and forces in the physical universe, the DT acts as a bridge [30]. The digital twin for lithium-ion battery reliability is established within the framework of digital twins. Key components of the digital twin include data gathering, data management, modeling management, simulation and calculation, modeling evolution, visualization, and so on. Disregard is given to the mechanical integrity of the device as a result of fatigue, cracking, and structural alterations caused by discharge and charging rates. The chemical breakdown of lithium ions is assumed to be the primary cause of their loss.

Temperature plays a major role in the degradation of lithium-ion battery capacity during cycling. It has been hypothesized that the current contributes to the degradation of batteries in a roundabout way, via the production of heat and an increase in temperature. In order to model DT, a battery's physical components must be modelled at multiple scales and updated in real time. Instead of using a collection of coupled physical models to represent the battery, different models are used to reflect its various characteristics. What causes the battery to age, how hot it gets, and how it conducts electricity are all things that should be made clear. Therefore, a thorough battery DT requires the initial construction of multiple models, each with their own unique strengths and limits. Hybridization may be necessary since each model will serve a distinct function in the battery DT system.

Clustering is a method used in deep learning for classifying unlabeled data into meaningful categories. It is a method of organizing data by forming groups of records that share common characteristics, as one definition puts it. Possible related objects are kept together in a set that shares few or no characteristics with any other set. Clustering data based on a statistical model is called model-based clustering. A set of component models is supposed to have generated the observed data. Each model's probability distribution is a multivariate parametric distribution. Each observation is filed away in a specific group based on the subsystem that generated it. However, the parameters associated with each of the component distributed and the component that generates each observation are not known. The primary goal of proposed model learning is to identify the source of each data observation from the DT sensors, which provides a clustering of the data. In a perfect world, it would be reasonable to group together observations that share a common source. The proposed model framework is shown in Figure 3.

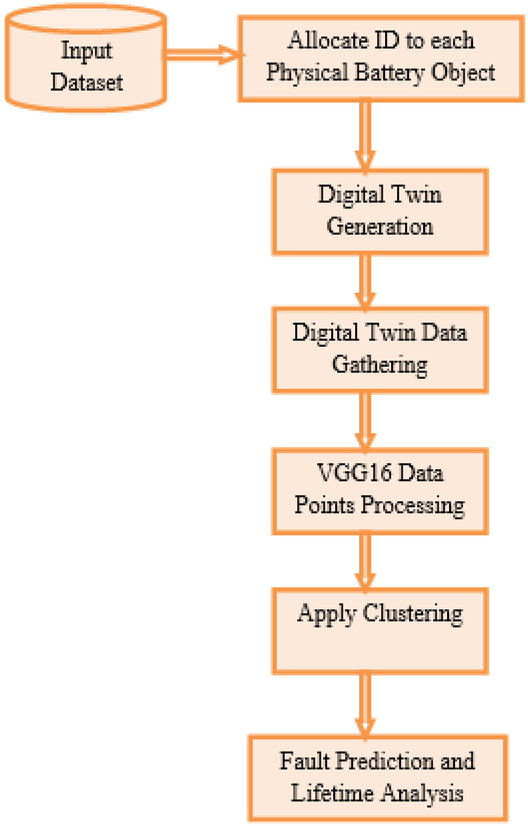

Fig 3: Proposed Model Framework

The processed text is provided as input to the cov1 layer with size as 3 x 3. After the text has been processed by a number of convolutional layers, it is next passed through filters with a very small responsive field: 3x3.The 1x1 convolution filters used in

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one of the combinations can be thought of as a transformation that is linear of the input channels. To ensure that the spatial data points are maintained after convolution, the convolution stride is set to 1 data point and the spatial padding of convolution layer input to 1x1 matrix for 3x3 convolution layers. Some of the convolution layers are followed by five max-pooling layers, which do spatial pooling. A max-pooling operation is carried out on a 2x2 pixel window at a stride of 2. Following a stack of convolutional layers, three Fully-Connected (FC) layers are used: the first two have 4096 channels apiece, and the third uses 1000 channels to achieve 2 way classification. The soft-max layer follows as the last one. All networks have the same layout for their completely connected layers. Every one of the hidden layers features a rectification (ReLU) non-linearity. The relevant query text is extracted by processing the entire big data returning the query text related information. This research proposes a Linked Clustering Model using VGG 16 for Lithium-ion batteries health condition monitoring (LCM-VGG-Li-ion-BHM). The VGG 16 model data processing is shown in Figure 4.

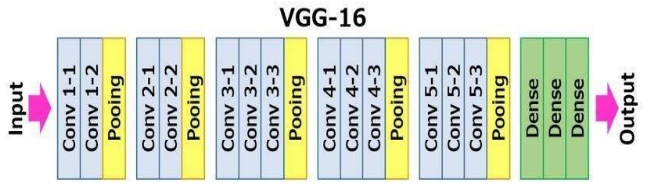

Fig 4: VGG 16 Data Processing Levels

Algorithm LCM-VGG-Li-ion-BHM

{

Input: Li-ion Battery Data $\{LB_{set}\}$

Output: Lifetime Prediction $LT_{set}\}$

Step-1: In the proposed model, Li-ion battery dataset is considered. To each sensor gathered data from a battery, an identity (ID) number is allocated. The ID is used to easily recognize the product and to identify the life time and fault. The ID allocation process is performed as

$$LBID[M] = \sum_{b=1}^{M} getattr(b) + maxattrset(b) + bstdid(b) + Th \tag{1}$$

Here getattr() is used to extract the battery attributes and maxattrset extracts the maximum value in the attribute set and bstdid is the physical object manufacturer number and Th is threshold value.

Step-2: A DT is an electronic copy created to be an exact duplicate of Li-ion battery. Sensors are installed in the object to collect data on its most important functions. Information on the object's energy output, temperature, environmental conditions, and more is gathered by these sensors. After being transmitted, this information is used to modify the digital replica. The DT creation of every physical Li-ion battery is performed as

$$DT(LIBID[M]) = \sum_{b=1}^{M} getLBID(b) + \sum_{b=1}^{M} \frac{setsimm(LBID(b)) + \gamma(b) + N^2}{count(LBID)} \tag{2}$$

Here LBID is gathered from the information stored and setsimm() is used to create a virtual environment of a current Li-ion battery with sensors used for gathering the fluid levels and N sensors are used for creating a copy of sensors for information gathering like temperature, charge and discharge levels are considered from the sensors.

Step-3: The sensors that are assembled in the batteries are used to gather the time at regular time intervals. These sensors will gather very useful sensitive information of Li-ion battery functionalities. The sensor data is transmitted to the central administrator for processing. The sensor data gathering and transmitting is performed as

$$Sdata[M] = \prod_{b=1}^{M} gettemp(b) + DT(\beta(b) + \mu(b) + \frac{R}{\delta(b)}) + k \tag{3}$$

Here gettemp() is used to gather the temperature of each Li-ion battery at regular time intervals, β is used for considering the charge levels, μ is used for gathering the discharge level, δ is used to gather the fluid levels in the Li-ion battery. K is the difference between the charge and discharge levels. R is the initial fluid level of the battery.

The data transmitting to central administrator is performed as

$$Bdata = \sum_{b=1}^{M} getmax(Sdata(b)) + getmin(Sdata(b)) - \tau(Sdata(b)) + \frac{Len(DT)}{len(Sdata)} \tag{4}$$

τ is the null values in the dataset gathered by the senor.

Step-4: For 3x3 convolution layers, keeping the spatial sensor data points after convolution requires setting the convolution stride to 1 data point and the spatial padding of convolution layer input to a 1x1 matrix. Five max-pooling layers, which do spatial pooling, follow some of the convolution layers. Max-pooling operation is performed on a 2x2 pixel window with a stride of 2. The VGG 16 model data point processing is performed as

Initially the probability data points of the Li-ion battery is represented as

$$Bdata[M] = \begin{bmatrix} D_1 \\ D_2 \\ D_3 \\ \vdots \\ D_M \end{bmatrix}$$

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$$Dproc[M] = \sum_{i=1}^{M}\sum_{j=1}^{i}\frac{\max(Bdata(b)}{len(Bdata)} + \lim_{i\to M}\left(\max(\beta) + \frac{\min(\mu)}{G}\right)^2 + hidlyr(Bdata(\max(\beta(b,b+1)) + \max(\delta(b,b+1)) + \frac{2*\omega}{stride} \quad (5)$$

Here ω is the kernel size, stride size is 1, hidlyr() considers the hidden layers for processing data points in each iterations.

Step-5: Clustering is a machine learning-based method for categorizing sets of data objects into groups with shared features. Clustering is a technique for organizing large sensor data sets into smaller, more manageable subsets, each of which contains only items with comparable characteristics. Therefore, clustering can be viewed as a multi-goal optimization issue. The clustering technique and optimal settings for its parameters must be tailored to each data collection and its eventual application. The sensor data point clustering is performed as

$$Clust(Dproc[M]) = \prod_{b=1}^{M} getVal(Dproc(b) + \frac{diff(Dproc(b,b+1))}{len(Bdata)} + \max(\delta(b))\begin{cases} V \leftarrow 1 \; if \max(\beta) \; and \min(\mu) \; and \max(\delta) \\ V \leftarrow 0 \quad Otherwise \end{cases} \quad (6)$$

Step-6: The data point after performing clustering process, defective points in each cycle, normal points in each cycle are clustered. Based on each cycle battery performance, the lifetime of the battery and malfunctioning is detected. The process is performed as

$$LTset[M] = \prod_{b=1}^{M} getmax(Clust(b,b+1)) + simm(Clust(b,b+1)) + \frac{max(\delta) + max(\beta)}{len(Clust)} - attr(min(Dproc(b))) \quad (7)$$

}

IV. RESULTS

Batteries will play a crucial role in many aspects of our future low-carbon environment, including electric vehicles and massive storage of energy on the electrical grid. It is still challenging to keep these devices in good working order and to maximize their potential. Given the recent progress made in understanding battery performance/lifespan, the variety of testing methods, and the emergence of ML approaches, it is clear that there is opportunity for more intelligent control of battery systems. To build a DT model, an enormous amount of historical data is required. It is possible to increase electrochemical comprehension and system identification by combining data from multiple sources, the NASA battery data collection being just one of many examples.

The development of a DT system to achieve dependable battery management requires these large volumes of offline data. But in the future, if a new type of battery lacks enough data, savvy algorithms will need to be used for transfer learning when building DT to expedite research on battery attributes. Another challenge to effective and trustworthy battery management is that the data collected in real-world applications is not as good as in laboratory conditions. The proposed model is implemented in Google Colab. The dataset is considered from the link https://www.kaggle.com/datasets/divyansh22/crystal-system-properties-for-liion-batteries?select=lithium-ion+batteries.csv.This research proposes a Linked Clustering Model usingVGG 16 for Lithium-ion batteries health condition monitoring (LCM-VGG-Li-ion-BHM). The proposed model is compared with the traditional Digital Twin in Smart Battery Management Systems (DT-SBMS). The proposed model when contrasted with the traditional model performs better in battery health prediction.

In the proposed model, the battery dataset is considered. For analysis, each battery data is allocated with an identity ID. This identity is used to analyze each batter data and the health status of battery and its life time and faulty batteries can be easily identified. The Li-ion Battery ID Allocation Time Levels of the proposed and existing models are shown in Table 1 and Figure 5.

Table 1: Li-ion Battery ID Allocation Time Levels

Dataset Records Considered	Models Considered	
	LCM-VGG-Li-ion-BHM Model	DT-SBMS Model
20000	9.4	17.3
40000	9.7	17.6
60000	10	18.1
80000	10.3	18.4
100000	10.6	18.6
120000	11	19

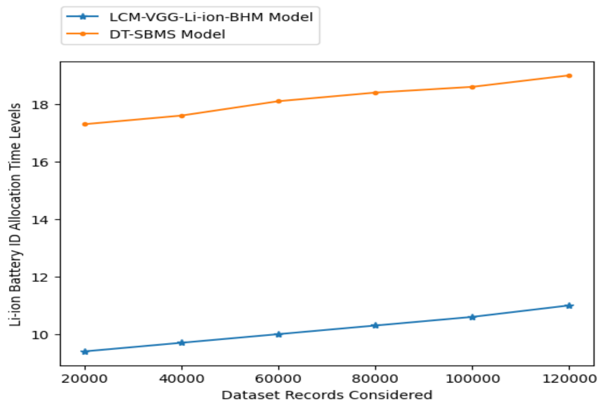

Fig 5: Li-ion Battery ID Allocation Time Levels

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A physical object's functionality, features, and behavior are digitally replicated in the virtual environment to create a digital twin of the physical asset. Smart sensors that gather data from the product are used to produce a real-time digital depiction of the asset. The Table 2 and Figure 6 shows the Digital Twin Creation Accuracy Levels of the proposed and existing models.

Table 2: Digital Twin Creation Accuracy Levels

Dataset Records Considered	Models Considered	
	LCM-VGG-Li-ion-BHM Model	DT-SBMS Model
20000	96.6	90
40000	96.7	90.2
60000	97.1	90.4
80000	97.4	90.7
100000	97.5	91
120000	97.8	92

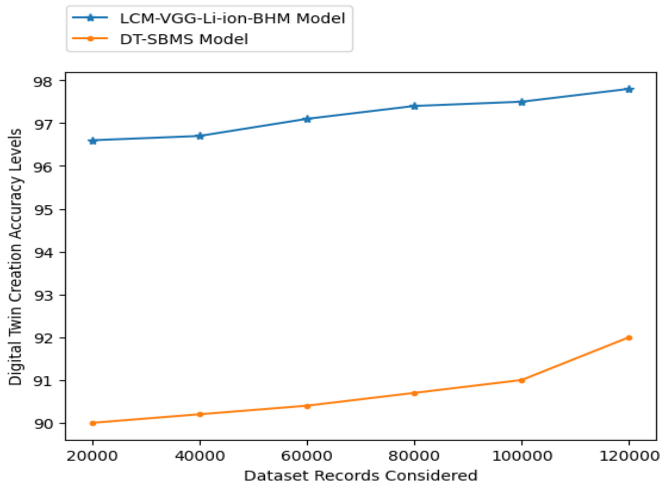

Fig 6: Digital Twin Creation Accuracy Levels

The sensors that are used to create a digital twin will gather data at regular time intervals. The data will be gathered by the central administrator for analysis. The data of each battery is gathered and this data is used to estimate the life time of the battery and for detection of faults. The Data Gathering Time Levels of the proposed and existing models are shown in Table3 and Figure 7.

Table 3: Data Gathering Time Levels

Dataset Records Considered	Models Considered	
	LCM-VGG-Li-ion-BHM Model	DT-SBMS Model
20000	14.8	19
40000	15.1	19.4
60000	15.4	20
80000	15.6	21
100000	15.7	22
120000	16	23

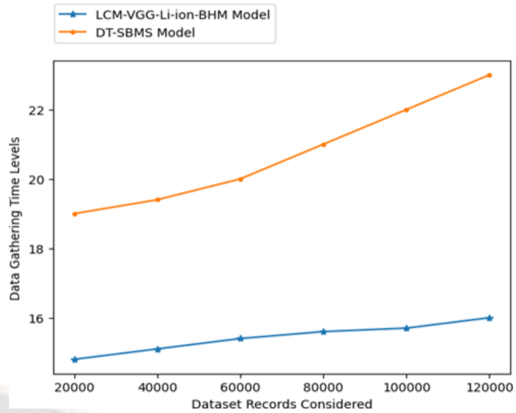

Fig 7: Data Gathering Time Levels

In contrast to AlexNet's huge receptive fields, VGG's are much smaller. Since the stride is 1, it employs a 3x3 grid for storing the values. With three ReLU units rather of one, the decision function can make finer distinctions. In addition, there are less parameters. The VGG 16 Model Data Processing Accuracy Levels of existing and proposed models are depicted in Table 4 and Figure 8.

Table 4: VGG 16 Model Data Processing Accuracy Levels

Dataset Records Considered	Models Considered	
	LCM-VGG-Li-ion-BHM Model	DT-SBMS Model
20000	95.4	90.2
40000	95.7	90.5
60000	95.8	90.6
80000	96.1	91
100000	96.4	91.3
120000	96.6	91.5

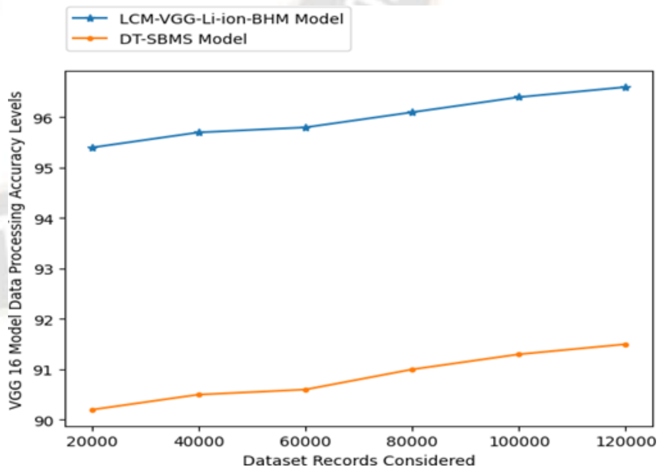

Fig 8: VGG 16 Model Data Processing Accuracy Levels

In databases with more than one observable variable, clustering helps to classify items into groups with shared characteristics. The key benefit of a clustered system is that it can recover automatically in the event of a breakdown. The term cluster analysis refers to the process of arranging battery data points so

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that no two clusters contain data points that are less comparable to one another. Data is clustered based on criteria such minimum distances, data point densities, graphs, and other statistical distributions. The Data Point Linked Clustering Accuracy Levels of the proposed and existing models areshown in Table 5 and Figure 9.

Table 5: Data Point Linked Clustering Accuracy Levels

Dataset Records Considered	Models Considered	
	LCM-VGG-Li-ion-BHM Model	DT-SBMS Model
20000	96.8	91.5
40000	97	92
60000	97.3	92.5
80000	97.5	93
100000	97.8	93.5
120000	98	94

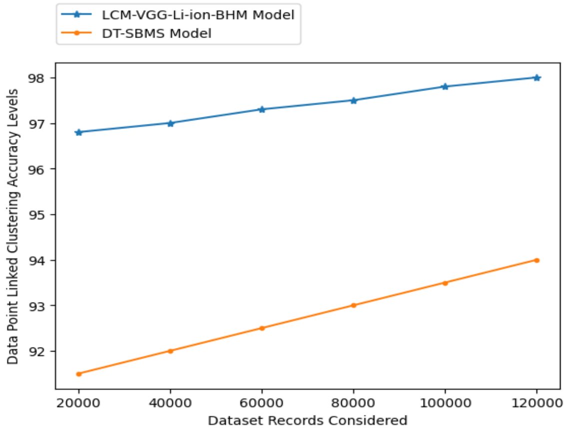

Fig 9: Data Point Linked Clustering Accuracy Levels

In order to guarantee the secure and dependable functioning of the battery system, fault diagnosis plays a crucial role in the battery management system by identifying problems at an early stage and delivering control measures to mitigate fault impacts. The Table 6 and Figure 10 represents the Battery Fault Detection Time Levels of the existing and proposed models.

Table 6: Battery Fault Detection Time Levels

Dataset Records Considered	Models Considered	
	LCM-VGG-Li-ion-BHM Model	DT-SBMS Model
20000	13.5	18.8
40000	13.7	19.4
60000	14	19.6
80000	14.2	20.2
100000	14.5	20.5
120000	15	21

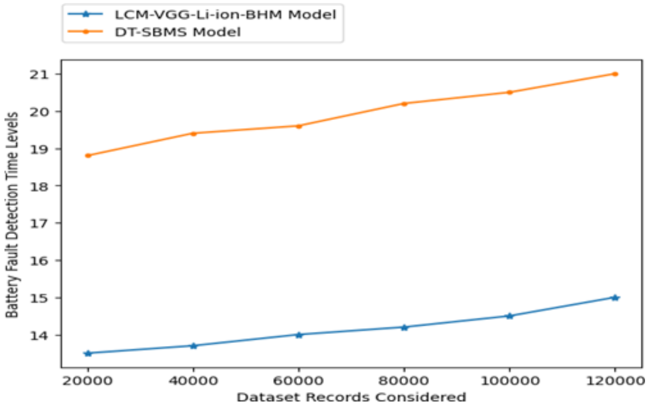

Fig 10: Battery Fault Detection Time Level

In data processing during numerous cycles, the VGG 16 model process the sensor data in multiple cycles for estimating the lifetime and for fault detection. The disorder in the data points willbe used for accurate health status checking. The Battery Health Prediction Accuracy Levels of the proposed and existing models are shown in Table 7 and Figure 11.

Table 7: Battery Health Prediction Accuracy Levels

Dataset Records Considered	Models Considered	
	LCM-VGG-Li-ion-BHM Model	DT-SBMS Model
20000	97.4	93
40000	97.6	93.5
60000	97.9	93.7
80000	98.2	94.1
100000	98.3	94.6
120000	98.5	95

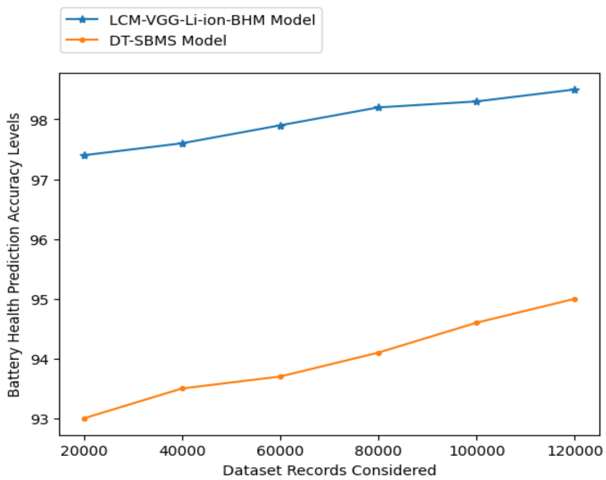

Fig 11: Battery Health Prediction Accuracy Levels

V. CONCLUSION

To all intents and purposes, DT technology can be used to produce and assemble batteries. Like an aeroplane factory, the DT-based virtual battery manufacturing line is efficient and effective. Several sensors placed along the production line or in the workshop might report their data to one central hub. Big data analysis is used to connect and analyze data among equipment and equipment, technology and system, and system and system in order to fully digitalize and depict the power battery assembling and production process. The logistics of introducing battery DT were examined. One of the challenges in implementing battery DT is ensuring that the model has access to relevant operational data pertaining to the battery lifetime. Although there may be initial expenditures and lengthy implementation timeframes, standardizing the data integration method for battery DTs in the next years is required. There is currently no tried and true method for changing model parameters during battery use, which is the second major challenge in applying DT to batteries. The results of this research imply that, if the battery parameters are tracked, they will continue changing after a certain period of time and a certain number of cycles. Improvements in representation, performance estimation, behavioral estimations, and optimization strategies are some of the advantages of battery DTs that is performed in this research. This research proposes a Linked Clustering Model using VGG 16 for Lithium-ion batteries health condition monitoring. This research shows that by analyzing the electrochemical consequences of the driving cycle on battery degradation, a battery DT can maximize the utilization of existing battery management system features.

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