



A novel disassembly process of end-of-life lithium-ion batteries enhanced by online sensing and machine learning techniques

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Received: 3 June 2021 / Accepted: 9 March 2022 / Published online: 20 April 2022

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Abstract

An effective lithium-ion battery (LIB) recycling infrastructure is of great importance to alleviate the concerns over the disposal of waste LIBs and the sustainability of critical elements for producing LIB components. The End-of-life (EOL) LIBs are in various sizes and shapes, which create significant challenges to automate a few unit operations (e.g., disassembly at the cell level) of the recycling process. Meanwhile, hazardous and flammable materials are contained in LIBs, posing great threats to the human exposure. Therefore, it is difficult to dismantle the LIBs safely and efficiently to recover critical materials. Automation has become a competitive solution in manufacturing world, which allows for mass production at outstanding speeds and with great repeatability or quality. It is imperative to develop automatic disassembly solution to effectively disassemble the LIBs while safeguarding human workers against the hazards environment. In this work, we demonstrate an automatic battery disassembly platform enhanced by online sensing and machine learning technologies. The computer vision is used to classify different types of batteries based on their brands and sizes. The real-time temperature data is captured from a thermal camera. A data-driven model is built to predict the cutting temperature pattern and the temperature spike can be mitigated by the close-loop control system. Furthermore, quality control is conducted using a neural network model to detect and mitigate the cutting defects. The integrated disassembly platform can realize the real-time diagnosis and closed-loop control of the cutting process to optimize the cutting quality and improve the safety.

Keywords Lithium-ion battery · Battery dismantling · Battery recycling · Machine learning · Online sensing

Introduction

The booming market of LIBs led to a three-fold increase in the price of lithium and a four-fold increase in that of cobalt between 2016 and 2018 (Pagliaro & Meneguzzo, 2019). Meanwhile, it will also bring huge amount of hazardous waste due to the end-of-life disposal of LIBs and create concerns over the long-term sustainability of critical elements for producing the major battery components. The growing use of LIBs is bound to exacerbate the problem in the near future

as the International Energy Agency estimates that global EV sales could reach four million in 2020 and 21.5 million by 2030, corresponding to an approximately 24% annual sales growth (Or et al., 2020). Therefore, it is essential to recycle the EOL LIBs and reclaim the valuable materials for environmental and economical sustainability. An effective recycling process helps to build a circular economy that can keep valuable or harmful materials out of landfills, leading to the efficient recovery of useful components in battery (Patel et al., 2017).

The first step of recycling is to pre-process (e.g., deactivate, disassemble or comminute) the EOL batteries and sort the battery components for recycling. The existing pre-processing uses mechanical processes like crushing and shredding to expose the valuable electrode materials for subsequent hydrometallurgical and pyrometallurgical processes (Herrmann et al., 2014; Pagnanelli et al., 2016). These processes have disadvantages such as the lack of lithium recovery, high output of liquid hazardous waste for wet crushing, and high energy input (Diekmann et al., 2017). In

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contrast, the efficient direct recycling process can realize the recovery and reuse of the battery materials directly in the supply chain for remanufacturing without breaking down their chemical structure (Sloop et al., 2018; Yang et al., 2019). Theoretically, everything inside the LIBs can be recycled through direct recycling process including the cathode material, electrolyte, separator, aluminum and graphite. Since the output of direct recycling is the battery grade material, one of the challenges is to precisely separate out the electrode material and purify the segregated materials. Tremendous amount of impurities like copper, aluminum is introduced into the EOL cathode material in the conventional crushing method, which makes the downstream recycling process much more difficult. Manual disassembly of EOL LIBs is not practical because the workers would be exposed to toxic substances such as cobalt, lithium, or organic electrolyte in the spent batteries and the risk of battery explosion. It is believed that exposure to these toxic chemicals results in significant negative health effects on workers (Fang et al., 2013). Meanwhile, it is costly, time-consuming and sensitive to noises. Therefore, the automatic disassembly without human intervention is preferred to take over the pre-processing of EOL battery for the direct recycling process since it presents high precision and processing speed. Due to the uncertainties of EOL products that increase the complexity of planning and operation, automatic disassembly of waste batteries is in limited use in recycling industry. It is necessary to promote the flexibility handling the uncertainty using intelligent solutions. Non-contact detection, classification, and quality control measurement, which offer advanced strategy planning for disassembly automation, has gained great attention in industrial manufacturing, would be the tendency of future battery recycling process.

We have demonstrated the prototype machinery that can dismantle the packaging of the mimic 2Ah LIB pouch cell and automatically sort various cell components (Li et al., 2019). In order to further improve the precision and accuracy of the disassembly, we plan to advance the demonstrated disassembling platform to cyber physical system (CPS) which integrates computing, communication and control to achieve collaborative and real-time interaction through feedback loops of interaction between computational processes and physical processes (Cheng et al., 2016). Machine learning-based data-driven approaches have demonstrated tremendous impact in a number of aspects involving image recognition and could potentially enhance the performance of CPS (Gu et al., 2019). Recognition is used to determine the existence of the components belonging to a particular type in a disassembly state (Buysens et al., 2013). Buker et al. (2001) combined the contour, gray value, and knowledge-based recognition to build the vision architecture which detected vehicle wheels and determined the exact position and pose of their bolts. Xu et al. (2019) used the convolutional operations on the indus-

trial images for material surface crack identification, and promising results have been obtained. Battery cells as well as their cutting sections have representative characteristics in terms of the color, geometry and size, which can be categorized using neural networks. The direct recycling requires destructive cutting to open the hermetic sealing of the cell meanwhile keep the stacking or winding structure (Harper et al., 2019). This mechanical cutting would inevitably generate heat which may cause the decomposition of the electrolyte salt LiPF_6 as well as damage the active material in cathode (Campion et al., 2005; Kraft et al., 2014). The machine learning predictive model is needed to monitor the whole process and predict the temperature trend. Effective measures should be taken to control the temperature under certain threshold by analyzing the historical data. For the control part, several researchers have investigated the methods on reducing the time delay and enhance robustness of the system. For example, a PD-type iterative learning control (ILC) algorithm for a class of discrete spatially interconnected systems with unstructured uncertainty (Zhou et al., 2020). In addition, the ILC has been used for discrete systems with multiple time-delays subjected to polytopic uncertainty and restricted frequency-domain (Tao et al., 2021). Optimization of parameters is needed to further improve the system, serving as the robust control system without long time delay in building the CPS.

In this work, we demonstrate a cyber-enabled and machine learning enhanced battery disassembly system, in which the computer vision is used to classify different types of batteries based on their brands and sizes. Combined with the real-time temperature data captured from thermal camera, a data-driven prediction model is built to predict the cutting temperature pattern. Then a close-loop control is implemented to avoid the temperature spike by adjusting the cutting variables timely. Furthermore, quality control is conducted using computer vision model to detect and mitigate cutting defects.

System architecture

The process flow chart of the battery disassembly system is described in Fig. 1. The first step of the process is to classify the battery according to its brand and determine its length in order to choose the appropriate machine settings for cutting. During the cutting process, there is a safety concern when temperature spikes. For this reason, it is necessary to monitor the temperature and prevent the spike from happening by adjusting the machine settings. Finally, after the cutting finishes, we use computer vision to assess the quality of the cut.

Convolutional neural network (CNN) is a deep learning technique that has produced promising results in solving

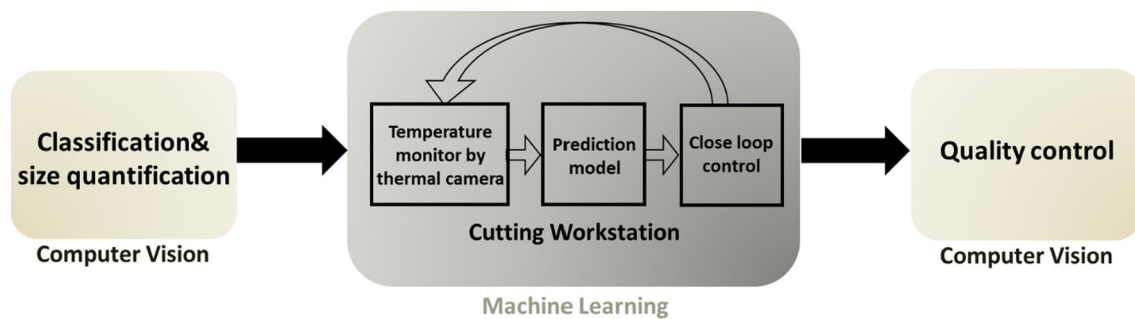


Fig. 1 The process flow chart for the cyber-enabled and machine

image classification by automatically discovering the representation needed for the task at hand (LeCun et al., 2015). The multi-layered neural networks can extract the feature of the pattern and are well-known for robustness to small inputs variations, minimal pre-processing and do not require any specific feature extractor choice (Kim et al., 2017). In this work, CNN image classification is used for both battery type classification and cutting quality control. For temperature monitoring, our goal is to predict the position of temperature spike and prevent it through feedback mechanisms to the machine. The control rules are derived based on the Design of Experiment results. For temperature spike prediction, we are using Long short-term memory (Hochreiter & Schmidhuber, 1997), which is a deep learning framework well suited for making predictions based on time series data.

The cutting station is built in the hood with ventilation (Fig. 2a) consisting of the step motor to feed the batteries into the bandsaw and the thermal camera mounted on the side. The spent phone battery (Fig. 2b) was shorted till the voltage is below 0.5 V. The shorting process can deactivate the batteries to release the residual energy for safe disassembly. Figure 2c illustrates the orthogonal cutting of the battery with the saw blade. The thermal image of the cutting process is shown in Fig. 2d.

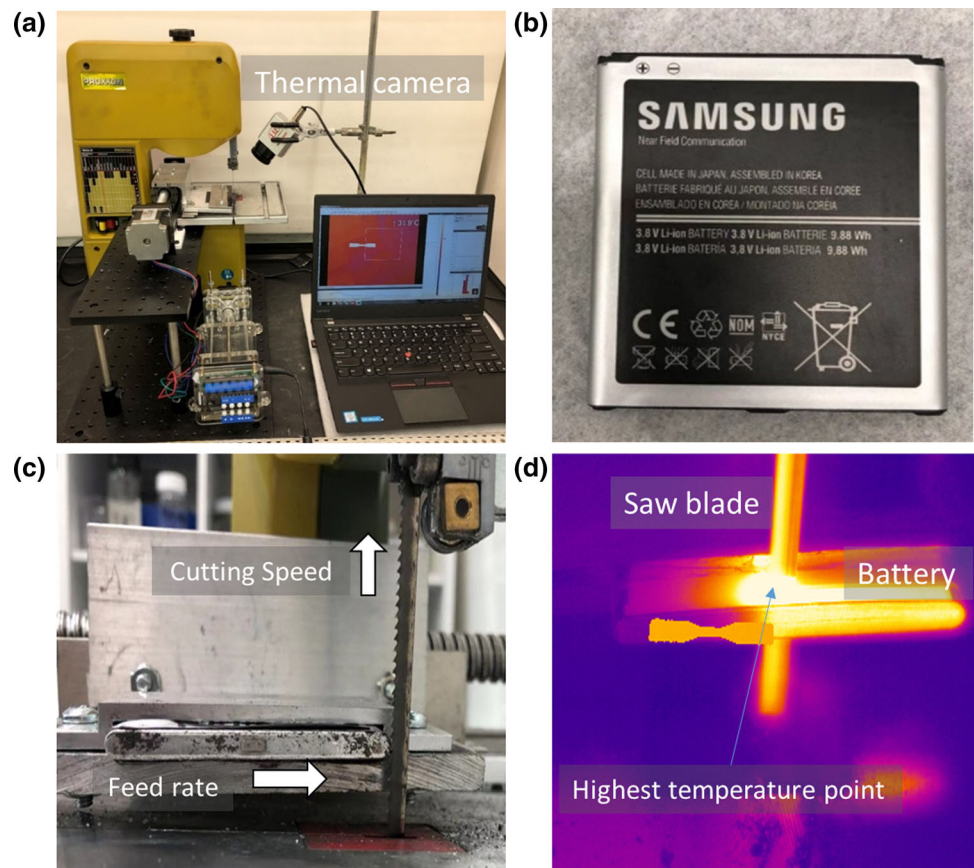
Vision-based battery classification

It is known that there are more than hundreds different types of LIBs in terms of the size, shape and brand model. In this chapter we give a demonstration to classify four common types of batteries, Samsung (97*41 mm), Samsung (62*57 mm), iPhone (94*38 mm) and iPhone (105*49 mm), by training a CNN classifier. Although only 4 types of batteries are demonstrated, the feasibility of applying CNN image classification in the battery sorting before recycling process is proved. In the real recycling process of spent batteries, the application scenario is more complicated in the following ways:

- (1) The number of battery types and battery sizes would be much more multitudinous.
- (2) The surface damage and deformation of the spent batteries will increase the difficulty of classification.
- (3) The classification method should be robust to the changes in illumination and battery placement.
- (4) As massive amount of the spent batteries needs to be treated, higher requirements are put forward for the speed and efficiency of classification.

CNN is widely used in the image-recognition field due to its outstanding classification capability (Krizhevsky et al., 2012). The aforementioned challenges make the application of CNN models in the real recycling process even more crucial. Given their representation learning power, CNN models can learn to recognize numerous types of batteries, and can generalize to different deformation conditions. Besides, the trained CNN model can efficiently and automatically predict the battery types at scale. They provide a great advantage in that both filters and classifiers for optimal feature extraction are automatically acquired learned from training data. In contrast, the optimal filters must be manually determined by intensive experiments for conventional supervised learning-based techniques such as support vector machine (SVM) and multi-layer perceptron (MLP) (Kim et al., 2017). A CNN consists of series of convolution, activation, and pooling feature extraction layers for automatically learning features followed by fully connected classification layers to classify an input image into desired categories. We have resized the input images to 100*100. The similar background of the images reduces the complexity of the recognition. There are some hyperparameters in a CNN model determining the network structure and settings, including the learning rate, number of epochs, batch size, depth of the network, etc. Hyperparameter tuning is the problem of finding the best set of model parameters based on the classification results of validation dataset before training starts. We have used Bayesian Optimization (BO) approach to find the best configuration of

Fig. 2 **a** The cell cutting station prototype equipped with thermal camera. **b** A cell phone battery with hard aluminum case. **c** The side view of the fastened pouch battery and blade. **d** Thermal camera view of the cell and the cutting blade during the cutting process



the deep networks. BO is a sequential global optimization of a black-box function f :

$$x^* = \operatorname{argmax}_{x \in X} f(x) \quad (1)$$

In which f denotes the network structure, and x is the tuned hyperparameters. BO uses a Gaussian process (GP) as the cheaper to sample surrogate model. We use a Gaussian process with the squared exponential kernel:

$$k(x, x') = \sigma^2 \exp\left(-\frac{1}{2l^2} \|x - x'\|^2\right) \quad (2)$$

In which σ^2 and l control the uncertainty and the rate of change. BO provides a framework to sequentially select the query points using acquisition functions and update the GP with the new observations. We use Upper Confidence Bound (UCB) acquisition function to select the next set of hyperparameters:

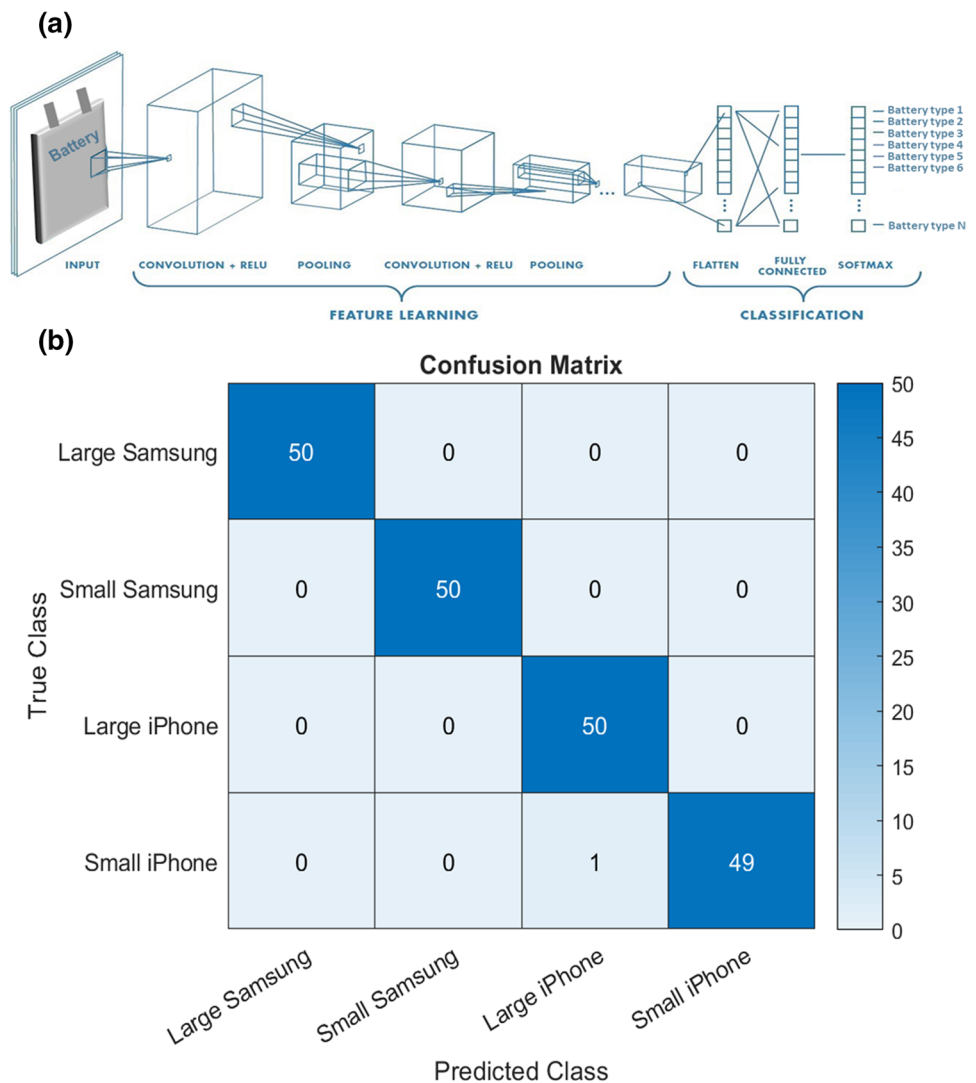
$$x_{t+1} = \operatorname{argmax} (\mu_t(x) + \kappa \sigma_t(x)) \quad (3)$$

In this formula, κ controls the trade-off between exploration and exploitation in the search strategy. μ_t and σ_t are the GP posterior distribution's mean and variance, respectively.

Our network structure automatically learns the most representative set of features for the classification task offline in the speed of about four frames per second on a single GPU. Once the CNN model is trained offline, it can perform image classification online faster, with high accuracy, and speed of about 30 frames per second on a single GPU. Although the number of battery types can be further augmented, this work is to explore the feasibility of applying the CNN method in battery classification in the industrial scale direct recycling of LIBs.

The database included the 300 Gy scale images from each of the battery types. The batteries were fully shorted before the image collection. 150 images from the database were used for training, 100 images for validation to tune hyperparameters, and the remaining 50 were used for testing. Based on the Bayesian hyperparameter tuning result, the hyperparameters are set as follows: Filtersize 3, Initial learning rate 0.0055, Momentum 0.85, Minibatch size 21, and L2 Regularization $2.71e-07$. Figure 3a shows CNN architecture adapted for battery type classification. Max stands for Max pooling and Avg is the Average pooling layer. The confusion matrix shown in the Fig. 3b provides the summary of the prediction result. Based on this confusion matrix, the instant online battery type classification has an **accuracy of 99.5%** on the test images, which is reliable when applied to the real battery

Fig. 3 **a** CNN architecture for battery type classification and its confusion matrix. **b** Battery type classification confusion matrix on the test set

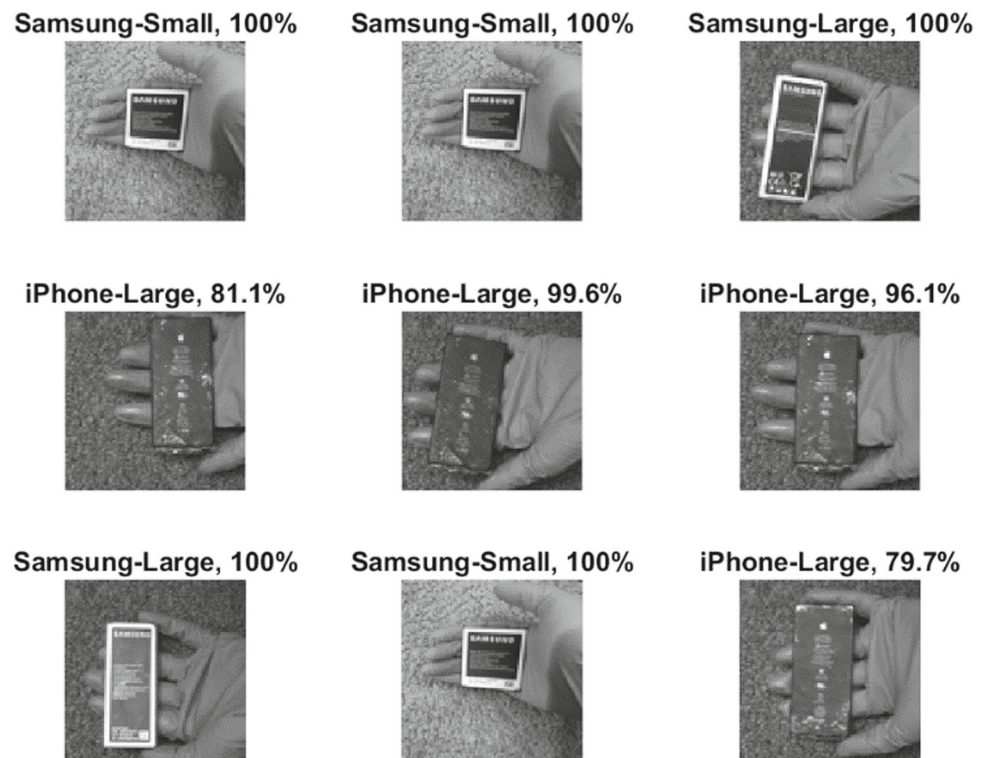


identification process. As shown in Fig. 3b, the classification only confuses small and large iPhones. Such errors can be eliminated given having fixed point of view. Figure 4 lists some test data of the classification model. The numbers on top of each image are the predicted class and their probabilities. The prediction performance across all classes can be observed from the confusion matrix (In Fig. 3b). We use these probabilities as a measure of certainty about the classification results (for battery size measurement as will be explained later). The certainty of the network about its prediction has to do with the distinctive features it can find in the image. If this probability is lower than 70%, we will conduct a secondary task of battery size measurement. A high accuracy is achieved for the 4-class classification with 300 Gy scale images after image augmentation (rotation, cropping, and flipping), but more images will be needed in a real scenario to have the same level of performance considering the different battery brands and types in practice. Even in that case, fine-tuning pre-trained networks (like ResNet and DenseNet) on Im-

geNet, and image augmentation are alternatives to lower the required data size. These approaches have proven successful in lowering down the data requirements in many applications. One example is recent works on Coronavirus CT scan images since only limited labeled data is available for training (Purohit et al., 2020; Wu et al., 2021). Although having more data is always desirable, generating large-labeled datasets is costly and, in many cases, impossible due to the nature of the work. Therefore, many works in the literature used the mentioned techniques (augmentation and using pre-trained models) to work with small datasets to present practical case studies.

After the classification, we can label each image based on its brand and size, which can be used to derive the actual size of the batteries. The width of the batteries is needed for normalizing the position data used in spike temperature prediction. All we need to do is to measure the battery size only once per category (only four times). The automatic battery size measurement is demonstrated here to provide an

Fig. 4 Some test images together with their predicted classes and the probabilities of those classes



alternative method when the battery type is not classified with high confidence (probability). Therefore, this step is carried out conditionally on the probability of the battery type classification. The measurement is through computer vision by calibration using a reference object (Rosebrock, 2017). The reference object should be of the known dimension and should be easily detected. An object that meets these two criteria is a coin placed at a known place in the image. As we know exactly the shape, size and placement of the coin (i.e., the location of the pixels that represents the coin), we can use it to find the pixels per metric of the image which is the ratio of the object width in the image to its actual width. We will first detect all the objects in the image using canny corner detection. Afterward, knowing the placement of the reference object (the coin), we can infer the size of all other detected objects using the found pixel per metric result. It is important to note that this method works under the assumption that we have a perfect 90-degree view. Figure 5 shows the result of this approach applied on the battery images.

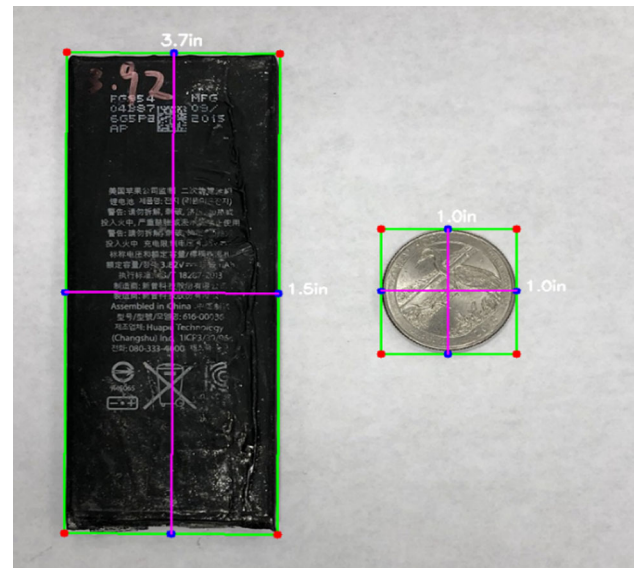


Fig. 5 Measuring the size of the battery by computer vision based on the reference object

Model-based battery disassembly system

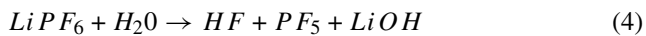
The objective of battery disassembly is to unpack the shells and extract the critical materials in a safe and efficient way. It can be believed that the electrolyte salt LiPF_6 decomposes near 70°C according to the Eq. (4) and generate toxic prod-

ucts such as HF and PF_5 . Some electrolyte solvents have an even lower flash point, as shown in the Table 1. Therefore, the maximum spike temperature is considered as an important parameter to be monitored during the disassembly process. To promote the safety and efficiency of disassembly process,

Table 1 The key temperature points of electrolyte components

Electrolyte component	Flash point	Boil point
Ethylene carbonate (EC)	150 °C	243 °C
Diethyl carbonate (DEC)	33 °C	126 °C
Dimethyl carbonate (DMC)	17 °C	90 °C
Ethyl methyl carbonate (EMC)	26.7 °C	104 °C

system parameters influencing the spike temperature deserve to be studied and optimized to offer optimal strategy that achieves balance between speed and safety during the cutting procedure. Design of Experiments (DOE) is a powerful data collection and analysis tool, which allows for multiple input factors to be manipulated, determining their effects on a desired output (response). Meanwhile, it can identify important interactions that may be missed when experimenting with one factor at a time.

**Table 2** The factors for cutting temperature

Factor	Name	Units	Low level (–)	High level (+)
A	Cutting speed	ft/min	536	820
B	Feed rate	mm/min	60	120
C	Tooth density	tooth per inch (TPI)	14	24

Table 3 Complete matrix, including interactions, with effects calculated

Standard	Main effect			Interaction effect				Response
	A	B	C	AB	AC	BC	ABC	
1	–	–	–	+	+	+	–	39.2
2	+	–	–	–	–	+	+	43.8
3	–	+	–	–	+	–	+	41.1
4	+	+	–	+	–	–	–	57.5
5	–	–	+	+	–	–	+	40
6	+	–	+	–	+	–	–	57
7	–	+	+	–	–	+	–	60.2
8	+	+	+	+	+	+	+	66
Effect	11.075	11.575	10.525	0.225	0.325	1.675	5.075	

Table 4 The analysis of variance (ANOVA) for maximum temperature

Source	Sum of squares(SS)	Df	Mean Square(MS)	F value	Prob>F
Model	734.82	3	244.94	17.06	<0.01
A	245.31	1	245.31	17.08	<0.01
B	267.96	1	267.96	18.66	<0.01
C	221.55	1	221.55	15.43	<0.05
Residual	57.43	4	14.358		
Cor Total	798.52	7	114.074		

The study of factors that influence the cutting temperature by design-of-experiment

Using the DOE method, the impact of different parameters on the maximum cutting temperature was investigated. The Samsung batteries with hard aluminum shells were fixed on the step motor by a clamp. The location of cutting was the front edge of the cell that carries the electrode tabs to keep the internal electrode-separator-compound (ESC) structure intact. Factors that affect the maximum cutting temperature are: cutting speed(A), feed rate(B) and tooth density of the blade(C). Each factor affecting cutting temperature is considered at low and high levels and shown in Table 2.

The results of the experiments were listed in Table 3, including the effect of the factors and their interactions. It can be observed that the cutting speed, feed rate, as well as the tooth density have significant positive effects on the cutting temperature. The analysis of variance (ANOVA) in Table 4 indicates that the actual F of 17.06 is bracketed by the critical value for 0.1% and 1% risk. We can say that we are

more than 99% confident that the maximum spike temperature is significantly affected by factor A, B and C. Among all the three factors, the tooth density and the cutting speed can be reduced to the minimum within the scope of conditions to lower the processing temperature. The confliction lies on that lowering the feed rate could decrease the cutting temperature but it also loses efficiency (i.e., number of batteries treated per minute). Therefore, the feed rate needs to be controlled in an optimized strategy to realize the balance between efficiency and safety.

Temperature spike position prediction

Temperature spike is a primary safety concern during the battery cutting. Based on the temperature evolution data collected by thermal cameras, this temperature spike often happens near the end of cutting. Figure S1 in Supplemental Information shows some examples of the temperature evolution patterns during the cutting process. Our goal is to predict the location of this spike in order to implement preventative measures by adjusting the parameters of the machine through a closed loop control system. Long short term memory (LSTM) is a widely used time series prediction method introduced to solve the vanishing/exploding gradient problem of recurrent neural networks (RNNs) (Graves et al., 2013) and is capable of learning long-term dependencies. LSTM replaces all the hidden units in RNN with LSTM cell and introduces a new element called cell state, which is a vector that goes through the LSTM cells at each of the next time steps to be modified. The LSTM unit (Fig. 6a) has three built-in mechanisms (gates). The forget gate, denoted as f , decides how much of the former cell state to throw away. The input gate, denoted as i , updates the old cell state using new inputs. Finally, the output gate, denoted as o , filters the final cell state to present as the output. The previous hidden state h_{t-1} and the current input x_t are used by these gates as specified in the following equations:

$$i_t = \sigma(W_i \cdot [h_{t-1}; x_t] + b_i) \quad (5)$$

$$f_t = \sigma(W_f \cdot [h_{t-1}; x_t] + b_f) \quad (6)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}; x_t] + b_o) \quad (7)$$

σ denotes the sigmoid activation function and $\odot$ denotes element-wise multiplication. Each of the gates updates the cell state in the way that its name suggests. Equation (9) calculates the new memory c_t by forgetting part of the previous memory and inputting something new to it. g_t is the candidate input. Equation (10) calculates the new hidden state. The weight matrices and bias terms are learned during LSTM

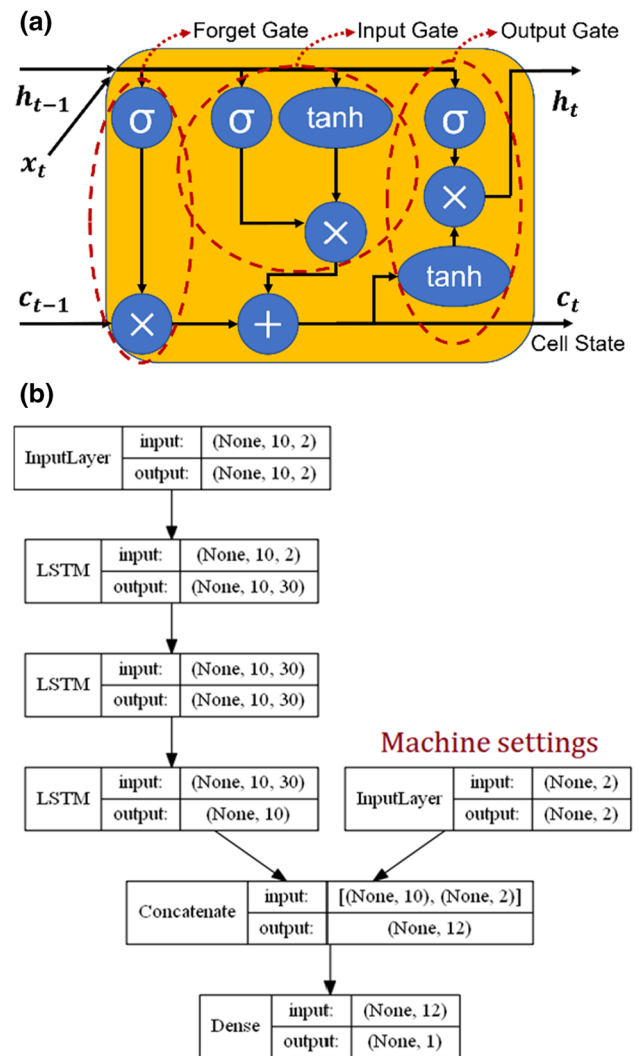


Fig. 6 a The block diagram of LSTM cell. b LSTM model structure for temperature spike position prediction. None at the first dimension indicates the flexibility of number of input samples

training. h_t is the hidden layer output of the LSTM unit at time step t , which is the input to the next LSTM unit.

$$g_t = \tanh(W_r \cdot [h_{t-1}; w_t] + b_r) \quad (8)$$

$$c_t = i_t \odot g_t + f_t \odot c_{t-1} \quad (9)$$

$$h_t = o_t \odot \tanh(c_t) \quad (10)$$

In order to use LSTM for temperature spike prediction, we first need to find the fitting data format and model structure. The data consists of temperature and its corresponding position (since the battery moves at constant feed rate, the position is in proportional with time series) as well as the machine settings for the cut. The first step was to convert the list of numbers in time series into the appropriate format

for supervised learning, which is a list of inputs and their corresponding outputs. Since the temperature spikes often happen at the end of the signal, we divide the whole cutting process into ten sections and developed the model to predict the temperature at the last 10% of the data series using the first 10% and find the position for the spike based on this prediction. Training the network on the sequence, rather than the single spike spot, provides more context for the network to learn from. Additionally, the sequence prediction gives the machine and the control system more time to adjust the parameters when it approaches the range of the spike position. We used a sliding window of 10 time steps to crop out both temperature and position time series and assigned to it a corresponding time point at the last 10% of the series. Therefore, the time series input has the shape of (10,2). In addition to the temperature time series data, we are feeding the machine settings consisting of speed and feed rate as other inputs to the model. Figure 6b shows the structure used for temperature spike position prediction. The input layer dimension (None, 10, 2) represent the flexible number of samples (batch size at the training time), number of time steps, and the temperature and position dimensions, respectively. After searching the hyperparameter space, we configured the LSTM to have 30-hidden states, batch size of 2 and epoch of 100. The middle LSTM layers output dimension in Fig. 6b is (None, 10, 30) since the model is configured to have 30 hidden states for each of the 10 time steps. The averaged prediction error over all the data using different indexes is reported in Table 5.

The LSTM prediction model presents great accuracy in terms of the spike position with quick response in this disassembly platform. It can be observed in Fig. 7 (a) that the maximum temperature monitored by thermal camera during

Table 5 Average prediction error based on different measures

Mean square error	7.40
Mean absolute error	1.62
Bias	− 0.69

the cutting process was illustrated in green line. The spike happened at the last 10% of the cutting duration, which was consistent with it of predicted results in green line.

Closed loop control

Figure 7b compares the temperature evolution patterns during the battery cutting process with and without the integrated closed loop control. It can be seen that the maximum spiking temperature is significantly reduced at the end of the cutting when the closed loop control is employed. The cutting speed, tooth density and feed rates are 536 ft/min, 14 TPI, 60 mm/min and 10 mm/min respectively. The feed rate is lowered down to 1 mm/min to mitigate the temperature spike before the motor reaches the predicted position. The LSTM prediction model was integrated into the disassembly system to analyze the real-time temperature data and the control system accurately decreased the feed rate based on the prediction results, e.g. the predicted position where the temperature spikes. Therefore, the temperature spike can be mitigated while the processing efficiency would not be influenced.

Figure 8a describes the structure of the closed loop control system. The step motor is connected to the board (SparkFun Stepoko), which is able to connect the computer to accept stepper motor commands. The real-time temperature evolution data during cutting process with respect to the battery position are recorded by thermal cameras (Micro-epsilon

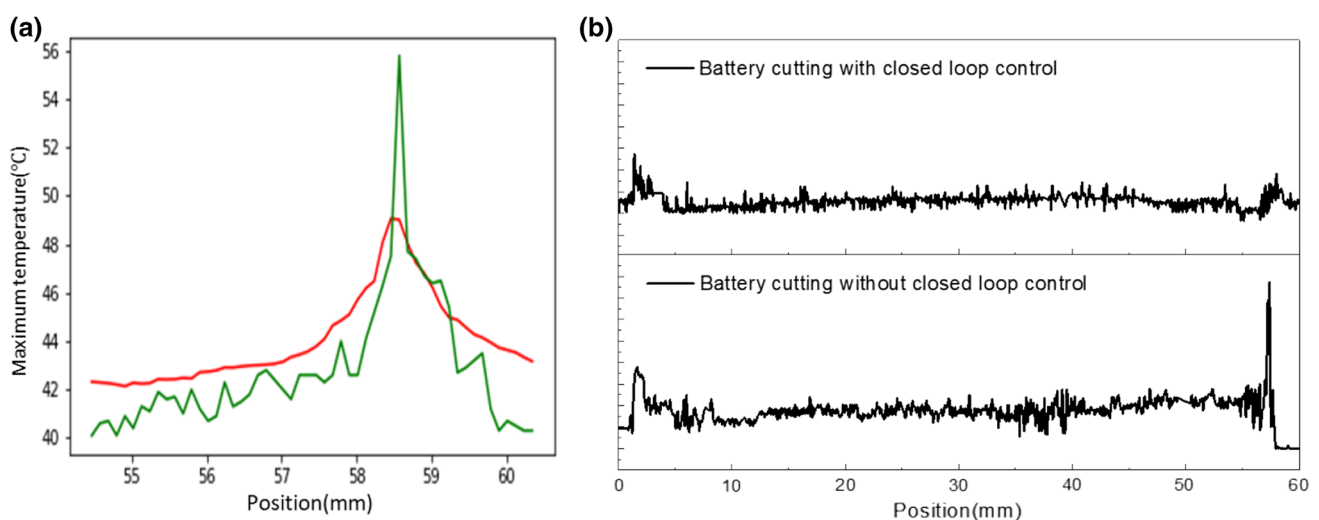
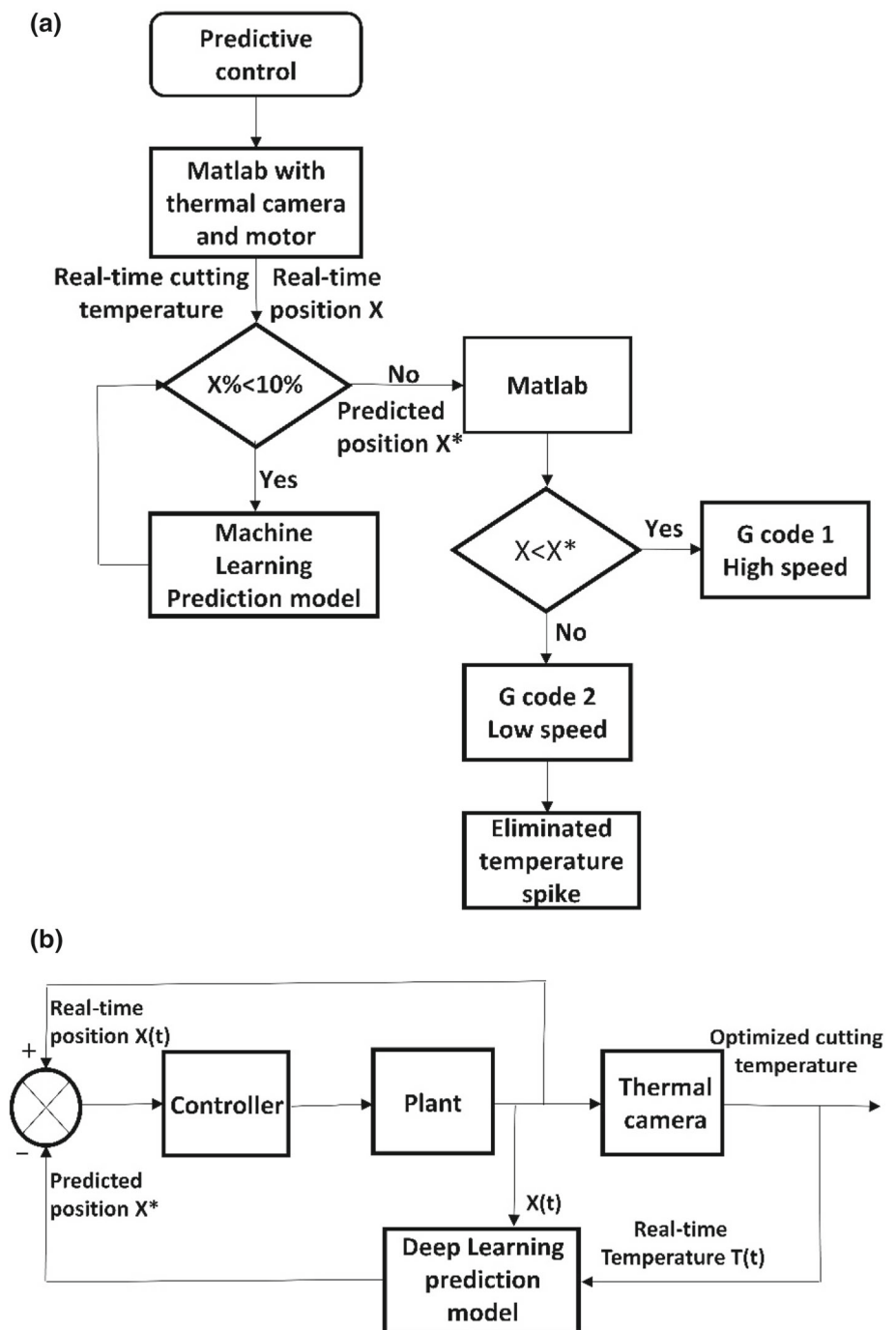


Fig. 7 **a** LSTM model prediction results in red vs actual values in green. **b** Maximum temperature data during the cutting process with or without closed loop control

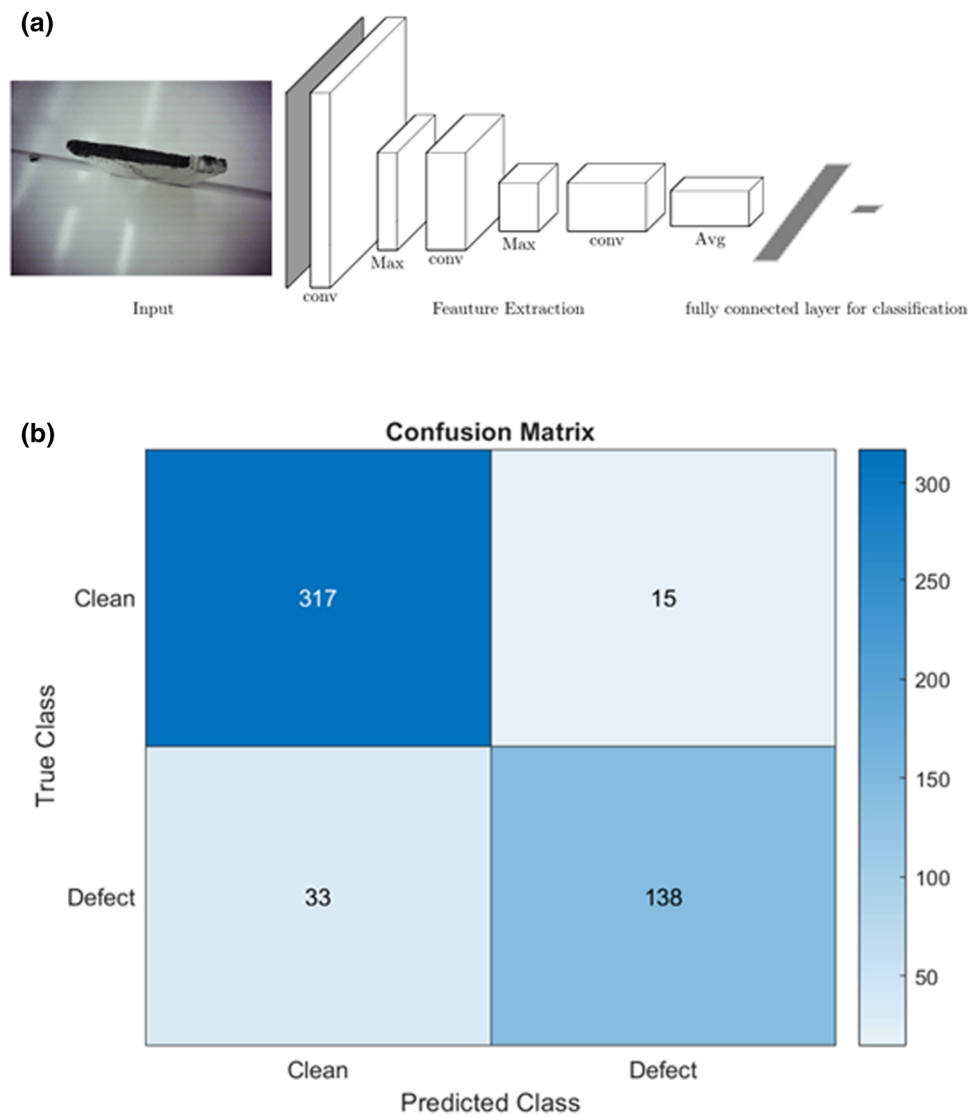
Fig. 8 **a** The structure of the closed loop model predictive control system. **b** The block diagram of the model predictive control feedback system



TIM300) and analyzed by the deep learning prediction model. We use an in-house Matlab code to transfer data to the predictive model and implement the control command to the hardware. It bridges the real-time interaction between computational processes and physical processes. When the battery position approaches the predicted position, the motor speed would be instantaneously decreased to effectively eliminate the temperature spike. The model predictive

control feedback system is shown in the Fig. 8b. Compared with other control methods, the model predictive control can achieve the behavior prediction ahead of time and overcome the response delay to control the machine parameters precisely (Han et al., 2013). It also balances the cutting time and process temperature to maximize the efficiency while ensure the safety.

Fig. 9 **a** The input image of defect cutting and the CNN architecture adapted for cut quality classification. **b** Cutting quality classification confusion matrix on the test set



Vision based quality control of cutting cross-section

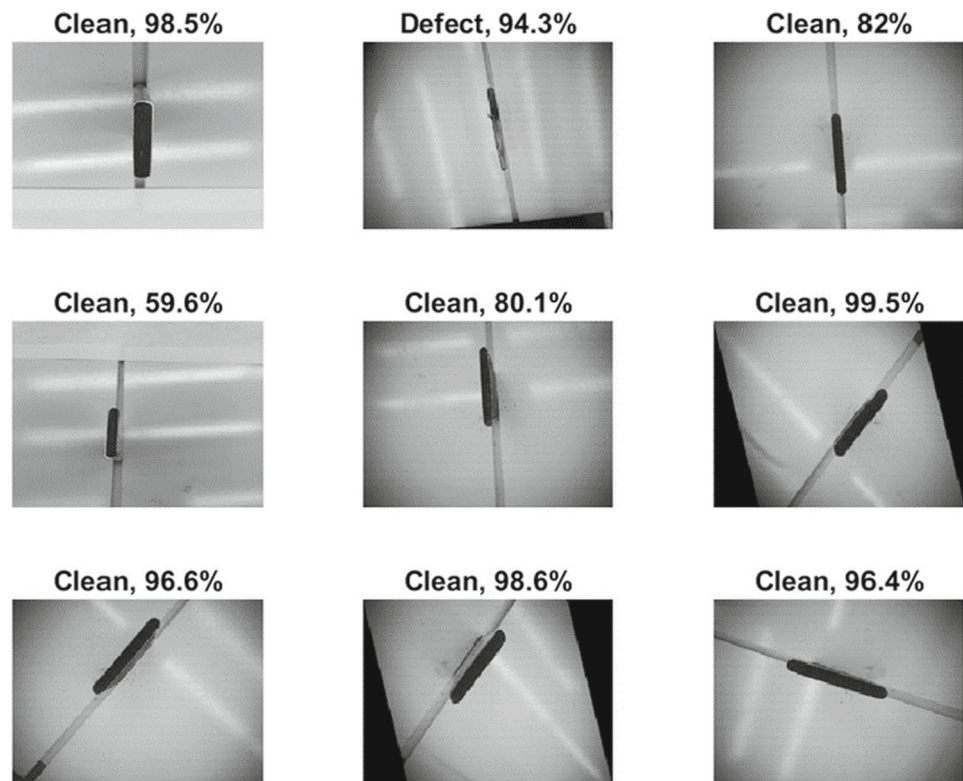
In this section, we attempt to detect defective cuts using convolutional neural network. The two classes of cuts are clean cut and defective cut. The database includes around 1100 RGB images with resolution of 640*480 from each label turned to gray scale and resized to the resolution of 150*200. 900 images from the database were used for training model, 100 images for validation to tune hyperparameters and the rest were used for testing. Based on the Bayesian hyperparameter tuning results, the best found hyperparameters for classifying quality of the cuts are: Filtersize 6, Initial learning rate 0.0051, Momentum 0.81, Minibatch size 22, and L2 Regularization 1.01e07. Figure 9a shows CNN architecture adapted for battery type classification. Based on the confusion matrix shown in the Fig. 9b, the clean or defective cut classification had the accuracy of 90.5%. Moreover, the

performance of this task should be measured with respect to defect recognition. In that regard, the defective class has been predicted with the precision (specificity) of 90.2% and recall (sensitivity) of 80.7%. Some tests of the recognition results are listed in the Fig. 10.

Conclusion

This work demonstrates a cyber-enabled and machine learning enhanced battery disassembly system. The spent LIBs were efficiently classified into certain brand and size by the trained computer vision model. The selected battery pouch cells with hard aluminum shell were used as test articles to demonstrate the effectiveness of the CPS system. Combined with the real-time temperature data captured from thermal camera, a data-driven prediction model was built to predict the location of the temperature spike. Then based on DOE

Fig. 10 Some test images together with their predicted classes and the probabilities of those classes of the quality control



results, the feed rate was precisely controlled to slow down before reaching the predicted position to avoid the temperature spike. Furthermore, quality control was successfully conducted using the neural network model to detect and mitigate the cutting defect. The CPS paradigm established for disassembling process can be used to improve the safety and quality control of other unit operations in the battery recycling process.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10845-022-01936-x>.

Acknowledgements This work was funded by the Department of Mechanical Engineering at Virginia Tech and Alfred P. Sloan Foundation under award G-2020-12651.

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