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Battery detection of XRay images using transfer learning

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Abstract. The need for detecting and sorting batteries is drastically increasing for many applications. This study proves the potential of transfer learning in predicting whether the image contains a battery or not, the location and identifying three types of batteries, namely: prismatic, pouch, and cylindrical Lithium-Ion Batteries (LIB). Particularly, it focuses on the transfer learning method in two applications: Training a large-scale dataset to detect electronic devices using a pre-trained YOLOv5m, then using these latter trained weights to detect and classify the batteries. The precision of battery detection achieves 94%, which outperforms the pre-trained YOLOv5m weights with 5%, in 22 ms inference time.

1 Introduction

Inner feature screening is commonly performed in food processing, medical images, and airport baggage inspection for prohibited products using XRay images. The major benefit of using this technique is that any damage, dirt, or corrosion on the surface of the object does not affect the detection prediction of the internal components.

Battery recycling became a global problem with the increasing consumption of electronic devices [1]. Proper collection, storage, and sorting of waste can reduce hazardous substances entering the soil, water, and human body as well as reducing the cost of recycling process. Besides, these batteries contain expensive metals like silver, zinc, and cadmium, which are rare Earth elements. Manual battery inspection and shredding could cause fire or lead-acid batteries that could leak when damaged [2]. Therefore, there is a need to tackle this problem using a smart and efficient strategy.

The rapid development in deep learning has enormously enhanced the ability to detect objects on images. Moreover, the ability of state-of-the-art deep learning structures boosts sorting accuracy, which surpasses human sorting efficiency. A study by [3], found that identifying and sorting various types of batteries using XRay technology can be solved through deep learning. Each battery type has unique regions that are automatically detected in XRay. The study identifies the battery type despite the condition of the device, whether there is no label or marking on the battery, or whether the battery is rusted. Their system can predict whether the device contains a battery or not, the location, and six

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types of battery technologies, namely: cylindrical nickel-metal hydride, cylindrical alkaline, cylindrical zinc-carbon, cylindrical LIB, pouch LIB, and button cell batteries, with an 89% precision and an 81% recall of battery detection using YOLOv2 using their small-scale dataset.

2 Implementation

Two experiments were conducted to detect whether there is an electrical device or not, the location of the battery and classifying the battery type, as shown in figure 1. The description of the used datasets and training the model using transfer learning will be described in this section.

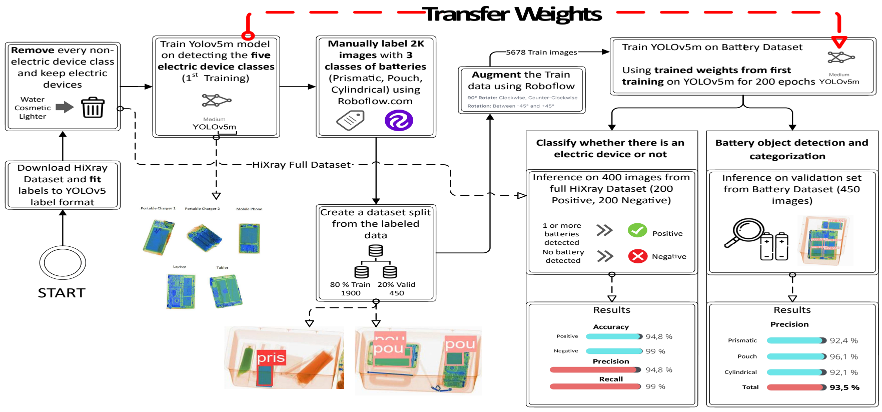

Fig. 1: Graphical abstract of the used method, implementation and results.

2.1 Datasets

2.1.1 Finding an appropriate dataset

The first step in preparing the experiment was to find an XRay images dataset with electronic devices that contains multiple types of batteries. There are three related datasets having at least one class of electronic devices: Durham DBF6 [4], PIDRay [5], and HiXray [6]. Since DBF6 dataset was not published as open-source and PIDRay contains one class of electronic devices (power bank), the HiXray dataset was the most suitable choice for our study. HiXray contains more than 45000 high-quality XRay images with 102.928 labels of 8 different object classes from an international airport.

2.1.2 Preparing the datasets for detecting the device and battery types

Three datasets were prepared, as shown in figure 2, and they are described as follows:

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- For the first experiment: To use the HiXray data, each label has been converted to the YOLOv5 text-format. Then, all the irrelevant labels were removed, which are water, cosmetic and non-metallic lighters. So, a total of 17500 samples were used, containing 15000 samples with at least one class and 2000 samples without electronic device, with split ratio 80% for training and 20% for testing.
- Creating the classification dataset for the purpose of sorting whether there is an electronic device or not. The set comprises 800 images of which 50% contain at least one electronic device class and 50% none.
- Creating the battery dataset with manual annotation: The resulting battery dataset contains 1900 training samples and 450 testing samples. For both, training and testing sets, there were 75% samples with at least one and 25% without any electronic device. RoboFlow [7] was used in this study for manual annotation of batteries by drawing bounding boxes around each one. As a result, 5175 batteries were labeled in a total of 2250 images. The ratios of battery classes existing in the samples were 10%, 50%, 40% for prismatic, pouch and cylindrical LIB cells, respectively. Data augmentation was applied as rotation $r \in \{-45°, +45°, -90°, +90°\}$ to show the model different variations of batteries that could be found in the real test.

DATASETS		HiXray Original
	Total number of samples	45.364
	Classes	Portable Charger 1 & 2, Mobile Phone, Laptop, Tablet, Water, Cosmetic, Metallic Lighter

	1st Training	2nd Training	Classification Dataset
Purpose	Train YOLOv5m with the original HiXray technical device classes	Train YOLOv5m on battery detection with transfer weights from 1st training	Classify whether there is at least one electronic device in the image or not
Train | Test Split	14.000 Train | 3.500 Test	5.678 Train | 450 Test	800 Test
Classes (Train amount | Test amount)	P. Charger (8.610 | 2.161) P. Charger 2 (5.395 | 1.350) Mo. Phone (16.400 | 4.032) Laptop (2.933 | 686) Tablet (1.527 | 414)	Prismatic LIB (1.290 | 86) Pouch LIB (6.074 | 567) Cylindrical LIB (4.182 | 426)	1+ Electronic Device (400) No Electronic Device (400)

Fig. 2: The prepared datasets for this study.

2.2 Transfer learning applications

For every training, YOLOv5m was used [8]. It is the state-of-the-art regarding real-time deep learning for object detection. It is the latest and the middle-weight version of YOLO algorithms and uses PyTorch framework rather than DarkNet. The main improvement to the family of YOLO models is the Focus layer that replaces the first three layers of YOLOv3 to reduce the required CUDA memory and increase the forward propagation and backpropagation,with pre-trained weights on the COCO dataset [9]. Battery detection is required for many real-time applications, like airport inspections, E-Waste recycling, etc.

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YOLO outperforms two-stage architecture like Faster R-CNN [10], Single Shot multi-box Detector (SSD) [11], and RetinaNet [12] in terms of speed and ability to perform real-time tasks accurately [13].
The following hyper-parameters were used throughout this study: Learning rate 0.01, image size 640x640, with augmentations of: translation 0.1, scaling 0.5, flip 0.5, and mosaic 1.0. For implementation, Google Colab was used with an NVIDIA Tesla P100-PCIE GPU.
In this study, transfer learning was applied in two phases:

- Transfer learning using YOLOv5 weights: For the first training, the first dataset was used to detect the electronic devices classes on the images, based on the HiXray classes. The first experiment was performed using the weights of pre-trained YOLOv5m on COCO dataset, on 20 Epochs with 32 batch-size.
- Transfer learning using the weights from the first training in:
  - Detecting the position and the battery class.
  - Predicting the presence of the battery in the third dataset. The model was trained for 200 Epochs with an early stop to prevent overfitting. When at least one battery has been detected from each image, the prediction was set to positive, otherwise, it was set to negative.

3 Results and discussion

For the first experiment of training YOLOv5m on the first dataset, performed on electrical devices only, the results are shown in table 1, and figure 3 (b). For the second experiment of using the previously trained weights (transfer learning), tested for battery detection. The combination of the results of table 2, and figure 3 (a), shows, that the transferred weights achieves an overall precision 94%, which outperforms the YOLOv5m weights. However, the cylindrical LIB has a relatively lower performance because they have small size, which could be confused with some noisy background objects. In addition, by using these weights, the classification of electronic and non-electronic devices are shown in table 3. The trained model for the second experiment took 22 ms for each inference, which is great for real-time testing.

The original HiXray dataset suffers from unbalancing where the dominance of

	PO1	PO2	Mobile phone	Laptop	Tablet	Total
Training	8610	5395	*16400*	2933	1527	34865
Validation	2161	1350	*4032*	686	414	8643
Precision on Val Data	**0.966**	0.96	0.939	0.899	0.936	**0.94**
Recall on Val Data	0.945	0.921	0.965	**0.99**	0.867	0.939
F1-Score	**0.955**	0.94	0.952	0.945	0.9	0.938

Table 1: Evaluation of electrical device detection.

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	Prismatic LIB	Pouch LIB	Cylindrical LIB	Total
Training	1290	*6074*	4182	11546
Validation	86	*567*	426	1079
	With YOLOv5m weights			
Precision on Val Data	0.818	0.962	0.899	**0.893**
Recall on Val Data	0.812	0.901	0.772	0.828
F1-Score	0.815	0.931	0.831	0.859
	With the transferred weights			
Precision on Val Data	0.924	**0.961**	0.921	**0.935**
Recall on Val Data	**0.948**	0.929	0.892	0.923
F1-Score	0.936	**0.945**	0.906	0.929

Table 2: Evaluation of battery detection using the YOLOv5 weights and our transferred trained weights.

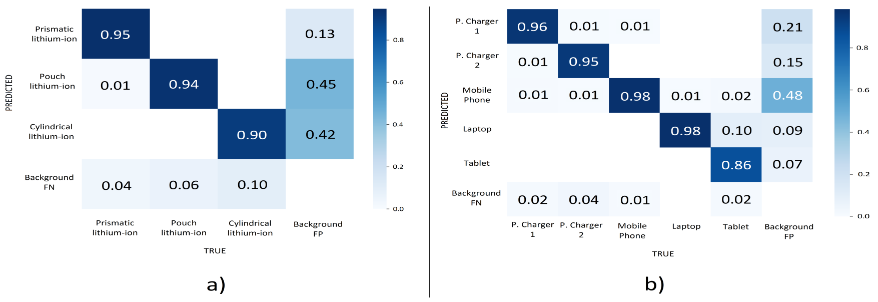

Fig. 3: Confusion matrices of object detection: (a) for batteries & (b) for electrical devices.

	Electronic Device	No Electronic Device
Accuracy on Validation Data	0.9475	0.99
Precision on Validation Data	**0.948**	
Recall on Validation Data	0.99	
F1-Score on Validation Data	0.969	

Table 3: Evaluation classifying the devices into electrical and non-electrical.

the mobile phone class exists in most of the images. Moreover, mobile phones, tablets, and most of the laptops in the images contain multiple pouch LIB cells. Therefore, it was not possible to achieve a numerical balance between the three battery classes. Furthermore, the occlusion of objects makes it difficult to manually label the batteries in some images and results in lower detection performance. Despite these challenges, previous results show that detecting electronic devices achieves 94% overall precision. Furthermore, the transferred weights outperform the YOLOv5m trained weights by 5% in detecting batteries and predicting the presence of electrical devices with 95% precision.

4 Conclusion

This study shows that transfer learning is an efficient method for detecting electrical devices and batteries in XRay images. Transfer learning was used in two experiments: Detecting electronic devices using the weights of the pre-trained YOLOv5m model with a total precision of 94%, then transferring these trained weights to detect and classify the battery with a precision of 94%, which shows that it outperforms the results of using the YOLOv5m weights with a precision of 89%, running 22ms for each inference. Moreover, the study achieves 95% of predicting the presence of electrical devices.

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