REAL-TIME OBJECT DETECTION FOR ELECTRONIC COMPONENTS

Katsuhiro Sasagaki

Under the supervision of Dr. Shukri Afazov

Contact: Katsuhiro.sasagaki2019@my.ntu.ac.uk

1. Introduction

Real-time object detection technologies based on image recognition have been used in industry and education in recent years [1, 2]. The aim of the project is to develop a real-time object detector for major electronic components on circuit boards, trained by deep machine learning techniques based on the Convolutional Neural Network (CNN) [3]. The challenge is to develop a practical trained CNN model that can deliver high detection accuracy in recognition of electronic components. Fig. 1 shows the concept of CNN [3].

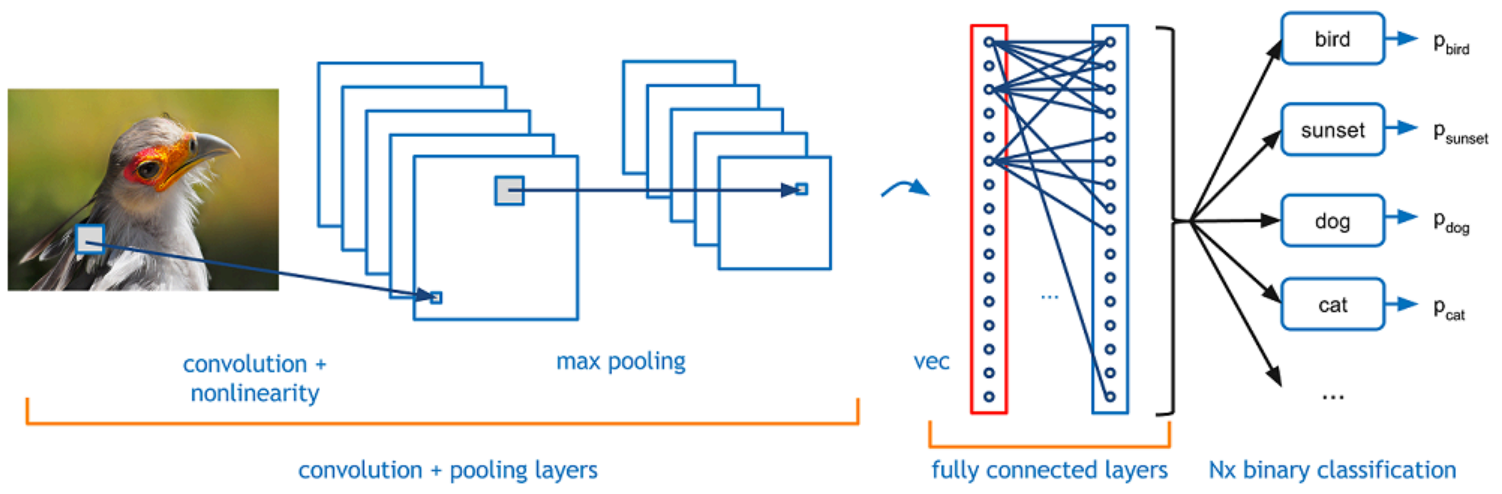

Fig.1: Concept of Convolutional Neural Network

2. Methods

Single Shot Multibox Detector Network Model

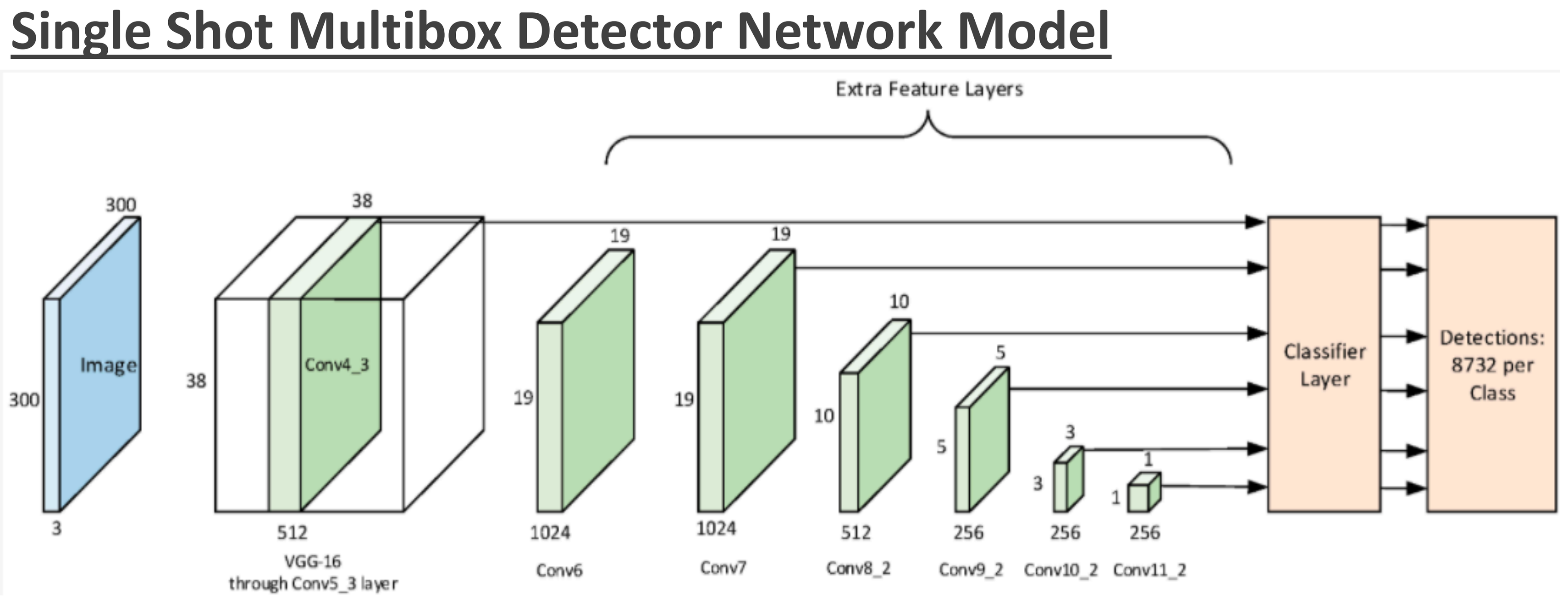

Fig.2: Concept of the Single Shot Multibox Detector [4]

The pre-trained model trained based on the Common Object in Context (COCO) dataset was used to reduce the total training time [5]. The main training was conducted by TensorFlow framework using image data. The electronic components were classified in ten classes and more than 2,000 images were used as shown in Table 1.

Table 1: Number of Images Gathered for Each Class

Capacitor	108 images	Relay	114 images
Diode	61 images	Resistor	114 images
IC	113 images	Transistor	108 images
Transformer	132 images	LED	130 images
Potentiometer	108 images	Inductor	132 images
High-dense PCB consisting of various components			980 images

Image augmentations are performed in the training for each image of the data set. This makes randomly some changes on the input images, such as rotating, resizing, distorting color, and adjusting brightness and contrast (see Fig. 3).

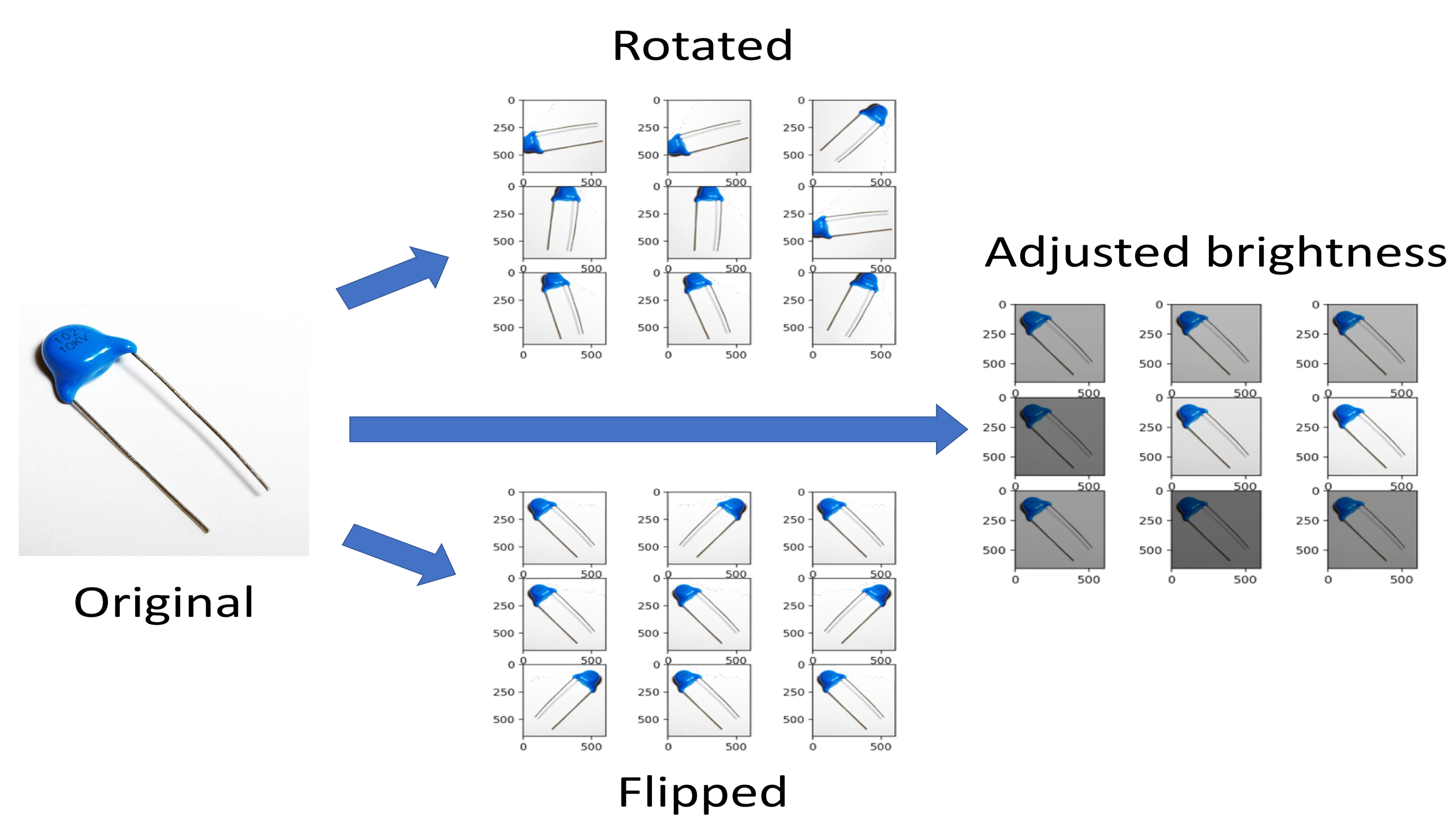

Fig.3: Example of Data Augmentation

3. Results

Detection accuracy of 100% and training accuracy of 83.5% were achieved at 120,000 steps of training.

- **Detection Accuracy Results (100% detection)**
  Detection accuracy can be visualized by the webcam inference and be measured by a ratio of the number of objects correctly detected to the number of objects expected. Since it depends on the object size, 100% detection can be achieved by bringing the webcam closer to the circuit board.

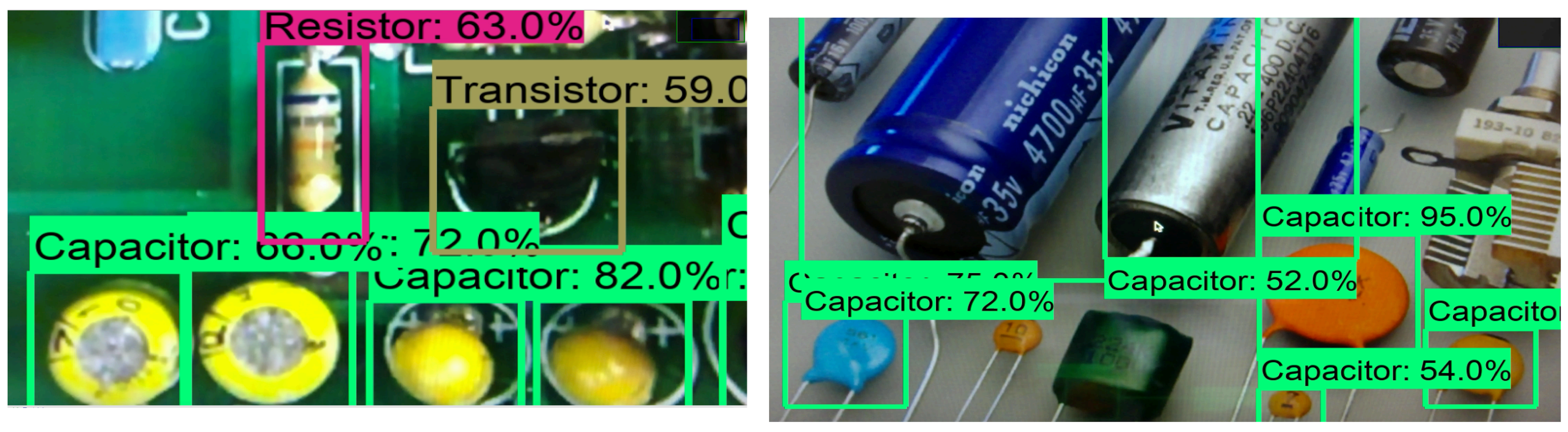

Fig.4: Visualized Results using Webcam

- **Training Accuracy Results (83.5% detection)**
  Training accuracy can be visualized by the TensorFlow evaluation script with some sample images (See Fig. 5-6). The accuracy value can be calculated as the Intersection of Union (IoU) (See Fig.7), which is a ratio of an over-rapped area between the detected and expected bounding boxes to the area of union between them [5]. In short, the more over-rapped area and less area of union, the higher detection accuracy.

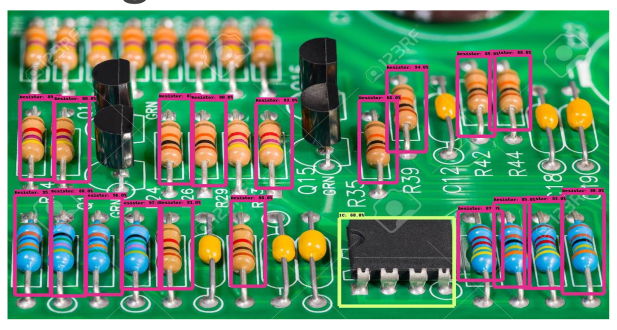

Fig.5: Visualized Results

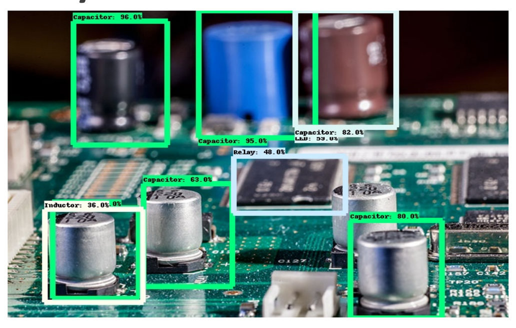

Fig.6: Visualized Results

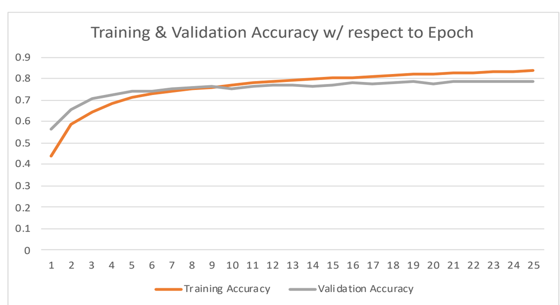

Fig.7: Training Accuracy (IoU)

4. Conclusions

- Detection accuracy of 100% was achieved by webcam inference and training accuracy of 83.5% was achieved using sample images.
- It was found that larger objects can be detected 2 to 3 times easier than smaller objects as a result of experiment. Therefore, higher precision is achieved when the webcam is brought closer to the circuit board, hence detection accuracy.
- Further investigation is needed to understand how to set-up and train the CNN models for smaller objects in size and high-dense circuit boards as a future research.
- The technology can be implemented in electronics manufacturing for quality control. It can be also used as a virtual lab for conducting online training sessions to students.

References

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