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Research Article

Electronic Components Detection Using Various Deep Learning Based Neural Network Models

Fatih UYSAL*

Kafkas University, Faculty of Engineering and Architecture, Department of Electrical and Electronics Engineering, 36100, Kars-Turkiye
* **Corresponding Author Email:** fatih.uysal@kafkas.edu.tr - **ORCID:** 0000-0002-1731-2647

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Abstract:

Electronic components of different sizes and types can be used in microelectronics, nanoelectronics, medical electronics, and optoelectronics. For this reason, accurate detection of all electronic components such as transistors, capacitors, resistors, light-emitting diodes and electronic chips is of great importance. For this purpose, in this study, an open source dataset was used for the detection of five different types of electronic components. In order to increase the amount of the dataset, firstly, data augmentation processes were performed by rotating the electronic component images at certain angles in the right and left directions. After these processes, multi-class classifications were performed using five different deep learning based neural network models, namely Vision Transformer, MobileNetV2, EfficientNet, Swin Transformer and Data-efficient Image Transformer. As a result of the electronic component detection processes performed with these various deep learning based models, all necessary evaluation metrics such as precision, recall, f1-score and accuracy were obtained for each model, and the highest accuracy value result was obtained as 0.992 in the Data-efficient Image Transformer model.

1. Introduction

Different electronic components of various types and sizes can be used in fields such as microelectronics, medical electronics, nanoelectronics and optoelectronics in relation to the field of electronics, which has a great importance in Electrical and Electronics Engineering, one of the engineering branches. One of the most important of these components is transistors. Examining at the development of transistor technology, vacuum tube diodes and vacuum tube triodes were developed in the early 1900s, while field-effect transistors (FETs) and bipolar transistors were developed in the 1920s and 1940s, respectively.
When the development of FET transistors is examined until today, it is observed that there are developments such as Metal-oxide FET, Complementary Metal Oxide Semiconductor (CMOS), Moore's law, Silicon on insulator (SOI), Strained silicon, High-k and Metal Gate Transistor (HKMG), FinFET, Stacked nanowire and Stacked nanosheet. Examining at the development of bipolar transistors until today; Germanium point-contact transistor, Bipolar junction transistor, Heterojunction bipolar transistor, Theory of the heterojunction bipolar transistor, Germanium integrated circuit, Silicon integrated circuit and SiGe heterojunction bipolar transistor developments have been realised respectively. Comparing the development of bipolar transistors and FET transistors, the latest and most important developments were achieved in 1987 with SiGe heterojunction bipolar transistors for bipolar transistors and with Stacked nanowire and Stacked nanosheet based transistors for FET transistors, which are still being developed today [1].
When the microelectronics field, which includes various electronic components, is examined, there are often devices containing components such as Metal-semiconductor field effect transistor (MESFET), Metal-oxide-semiconductor (MOS) capacitors and MOS field effect transistor (MOSFET). Devices related to optoelectronics include photodiodes, solar cells, light-emitting diodes (LEDs), laser diodes and heterojunction bipolar transistors [2].

Examining medical electronics, another field that involves electronic components, it is observed that a wide variety of devices are used. When the development of most devices associated with medical electronics is examined until today; Artificial kidney, X-ray, Electrocardiogram and Defibrillator in 1950s, Ultrasound, Glucometer, Flow cytometry and cell sorting in 1960s, Computer assisted tomography (CT), Endoscopy, Artificial hip and knee in 1970s, Magnetic resonance imaging (MRI), pulse oximeter and laser surgery in the 1980s, and positron emission tomography (PET), image-guided surgery, genomic sequencing and micro array developments have emerged since the 1990s [3].

When the electronic components and devices used in the field of nanoelectronics are examined, it is observed that Nanowire materials, Nanoelectromechanical systems (NEMS), Nanowire NEMS, Nanowire Electromechanical Resonators, Carbon nanotube (CNT) and CNT Y-Junctions [4]. In addition, there are materials and devices related to both electronics and optoelectronics using nanotechnology. When examining electronic devices that utilize nanotechnology, the following are included: Modulation-doped field effect transistor (MODFET), Resonant tunnel effect, Hot electron transistors (HETs), Resonant tunnelling transistors (RTT) and single electron transistor (SET).

Optoelectronic devices using nanotechnology are Vertical cavity surface emitting lasers (VCSELs), Strained quantum well lasers, Quantum dot lasers, Quantum well and superlattice photodetectors, Quantum well modulators, Heterostructure semiconductor lasers and Quantum well semiconductor lasers [5].

Within the scope of the study, detection processes were carried out with deep learning models using an open source dataset containing various electronic components. In this context, the main contributions and originalities of the literature are listed below:

- The dataset was not used in its raw form; instead, various data augmentation operations were performed on it.
- Multiple deep learning models were employed for electronic component detection, and the best classification model was identified.
- The number of classes used in electronic component detection was selected more than two and multi-class classification processes were performed.
- All important evalution metrics such as accuracy, recall, precision and f1-score, which are necessary for the correct analysis of the results, were obtained and the contribution to the detection results was clearly demonstrated.

2. Related Works

There are many studies in the literature where electronic components are detected with many different artificial intelligence approaches, especially deep learning. Using the dataset consisting of capacitors, potentiometers, and regulators, thanks to the Niryo Ned robotic arm and camera used in the study by Chand and Lal; Shallow Neural Network (SNN), Support Vector Machine (SVM), Principal Component Analysis (PCA) and the proposed Convolutional Neural Network (CNN) were used to perform classification operations, and the highest accuracy value was found to be 98.4% in the proposed CNN [6]. Soylu and Kaya used the deep learning-based MobileNet, Vision Transformer (ViT), Inception and EfficientNet models to classify electronic components, and the highest accuracy value of 96.21% was obtained in the ViT model [7]. As a result of the electronic component classification operations performed by Atik using an open source and three-class dataset containing capacitors, diodes, and resistors with four different deep learning-based models, namely GoogleNet, AlexNet, ShuffleNet, SqueezeNet, and the proposed CNN model, the highest accuracy value of 98.99% was found in the proposed CNN [8].

Varna and Abromavicius used various versions of convolutional neural networks based You Only Look Once (YOLO) model and SSD (Single Shot MultiBox Detector)-MobileNet models to classify and detect electronic components consisting of capacitors, resistors, diodes, and transistors, and the highest Average Precision (AP) value of 94.08% was obtained in YOLOv4 [9]. Cheng et al. used a Siamese Network model proposed as visual geometry group 16 (VGG-16) in the feature extraction part for the classification of seventeen different electronic components and by comparing the results with ResNet, GoogleNet, AlexNet, the highest area under the ROC (Receiver-operating characteristic) curve (AUC) score of 0.996 was found with the proposed model [10]. Zhou and Zhang proposed a 13-layer convolution neural networks model for electronic component detection and compared the results with deep learning based Xception and VGG models [11]. The highest Mean Average Precision (mAP) value obtained by Huang et al. using a deep learning model based on YOLOv3 is 95.21% using a dataset consisting of four different electronic components consisting of three capacitors with different values and one inductor [12].

Li et al. used YOLOv3 deep learning model to detect electronic components on Printed circuit board (PCB) and the results were compared with SSD and Faster Region Based Convolutional Networks (Faster R-CNN) and the highest detection result was found as 93.07% mAP in YOLOv3 based model [13]. By Chand and Assaf, the highest accuracy value was obtained as 99.62% with CNN as a result of classifications with VGG, ResNet, GoogleNet, EfficientNet, MobileNet and the proposed CNN model by passing the data containing electronic components through various preprocessing steps [14]. Guo et al. used a proposed deep learning model based on YOLOv4-tiny and SSD, RefineNet, Faster R-CNN, YOLOv4, EfficientDet models to detect 20 different types of electronic components in real-time and the highest mAP value was found to be 98.6% in the proposed model [15]. The highest AP value obtained using the YOLOv5 based deep learning model proposed by Chen et al. to detect 10 different types of electronic components on PCB is 38.3% [16]. Glucina et al. obtained the highest mAP of 99.5% as a result of the detection processes performed with YOLOv5-based deep learning models using an open-source shared PCB dataset with 13 classes containing various electronic components [17].

Using two different PCB datasets, the highest AP value found by Sharma and Kumar with the YOLOv3 model for the detection of electronic components is 79.1% [18]. Osmani et al. proposed a transfer learning model called VoltaVision, which aims to classify electronic components and compared with VGG, ResNet models and the highest accuracy value of 95.2% was obtained in the proposed model [19]. The highest mAP value found by detecting electronic components with the YOLOv7 deep learning model developed by Luo et al. using open source PCB dataset is 94.4% [20]. As a result of the classification processes performed with VGG, Xception, Inception, ResNet and Custom model using the dataset with 10 different electronic component classes obtained by Hożyń, the highest accuracy was obtained as 99.03% with the ResNet-based model [21]. In defect detection operations performed with the deep learning based model proposed by Weiss et al. using a dataset consisting of three different electronic components, namely capacitor, resistor and small outline transistor (SOT), over 90% accuracy value was obtained in each class [22]. The highest mAP value obtained by Yining and Honglei using a dataset consisting of four different electronic component classes, namely chip, electronic board, electrical connection piece, electronic slice, with YOLOv5 based deep learning model was 96.7% [23].

The highest accuracy values obtained by Surmeli and Ekenel with a ViT-based deep learning model called ViT-Mini for binary classification and multiclass classification with six classes in the dataset containing electronic components on PCBs are 99.46% and 96.52% for binary and multiclass classifications, respectively [24]. Lu et al. found a mAP value of 98% with the YOLOv3 deep learning model using a dataset consisting of six different classes of electronic components used in PCBs: film capacitor, inductor, aluminium electric capacitor (AEC), microchips, resistor and transistor [25]. Liu et al. used YOLOv8n based focusing dynamic channel-YOLO (FDC-YOLO) model for waste detection in a dataset consisting of electronic components and obtained a mAP value of 93.8% [26]. The highest mAP value obtained by Mohsin et al. for the detection of electronic components on waste PCBs using YOLOv8, YOLOv9 and Real-Time Detection Transformer (RT-DETR) deep-based models is 99% [27]. With the EfficientNetv2-L-YOLOv4 deep learning model proposed by Chi et al. for the detection of integrated circuits (ICs) on PCBs, a mAP value of 98.23% was obtained [28].

In the literature, it is observed that deep learning based VGG, MobileNet, DenseNet, YOLO and ViTs are mostly used for the detection of electronic components. In this study, unlike the majority of the literature, multiclass classification studies were carried out for electronic component detection with five different deep learning models by using data augmentation on open source dataset.

3. Materials and Methods

Within the scope of the study, a dataset shared as open source from the Kaggle platform and containing electronic components with 5 different types of classes was used as a dataset [29]. The classes in this dataset containing electronic components are Capacitors, Chips, LEDs, Resistors and Transistors. The initial values of the amount of the dataset are 100 for each class and 500 in total. For the training of deep learning models, the dataset was augmented by rotating the electronic component images for each class to the right and left at certain angles. After these data augmentation steps, the amount of the dataset was increased by 300 for each class, totalling 1500 in total. Thus, the amount of dataset was tripled compared to its initial state. For the deep learning models used in the study, the dataset was divided into 75% training and 25% validation. Thus, a total of 1125 electronic components, 225 in the training phase and 375 electronic components, 75 in the validation phase, were used in each class. These quantities for the initial and final versions of the dataset quantities are shown in figure 1. When figure 1 is analysed, it can be seen that the initial amount of data for each electronic component class, which was equal to 500 in total, was increased by 1000 images in total by performing data augmentation operations twice as much as the initial amount for each class and as a

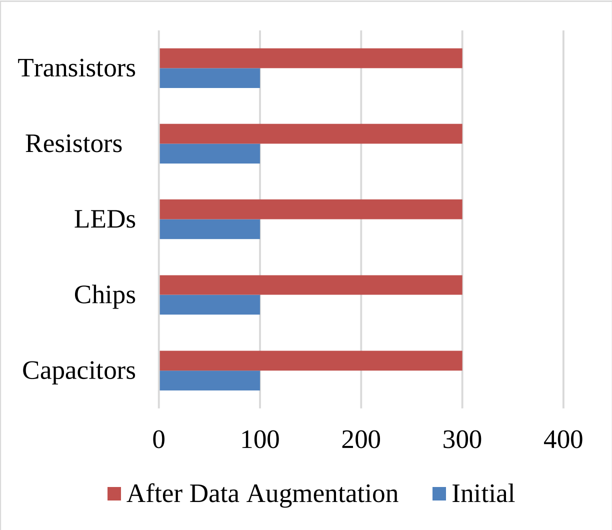

Figure 1. *Electronic components dataset amount distribution after initial and data augmentation*

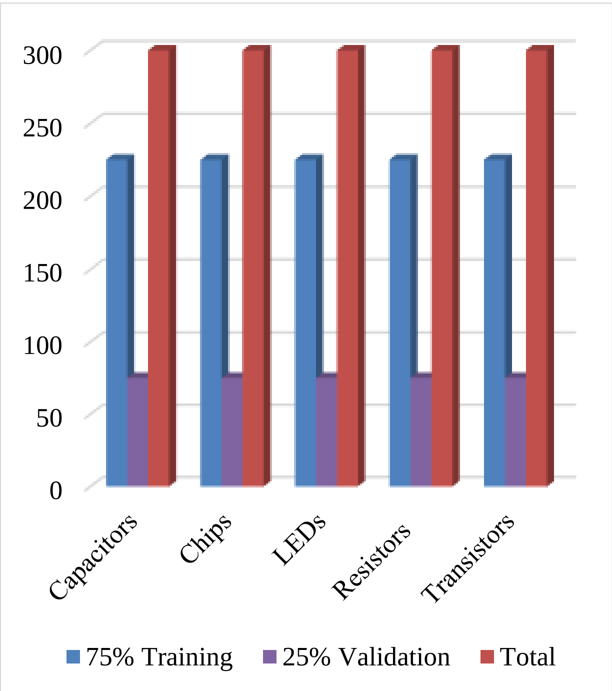

Figure 2. *Training and validation distribution in electronic components dataset*

result, 1500 electronic component data sets were obtained. The distribution of the training and validation parts of the dataset is given in figure 2. When figure 2 is examined in detail; it is observed that the total amount of electronic components corresponding to 25% validation distribution percentage in each class is 375 and the total amount of electronic components corresponding to 75% training distribution is 1125. Figure 3 shows sample electronic component images for each class. When figure 3 is analysed, it is observed that for each class of the dataset used for electronic components, there are images of different sizes, different shapes and different directions. Within the scope of the study, 5 different deep learning models, namely Vision Transformer (ViT), MobileNetV2, EfficientNet, Swin Transformer and Data-efficient Image Transformer (DeiT), were used to detect electronic components belonging to different classes. The related flowchart is given in figure 4.

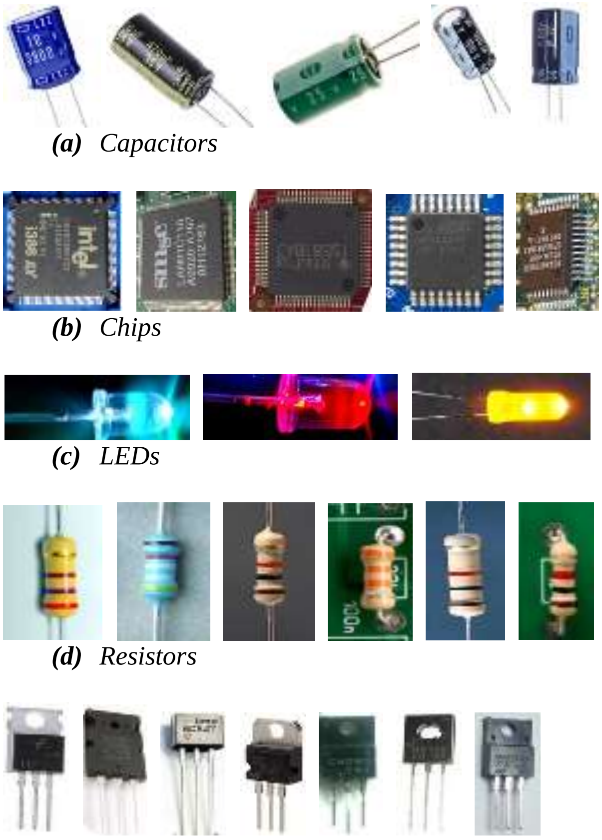
(a) *Capacitors*
(b) *Chips*
(c) *LEDs*
(d) *Resistors*
(e) *Transistors*

Figure 3. *Samples of electronic components classes*

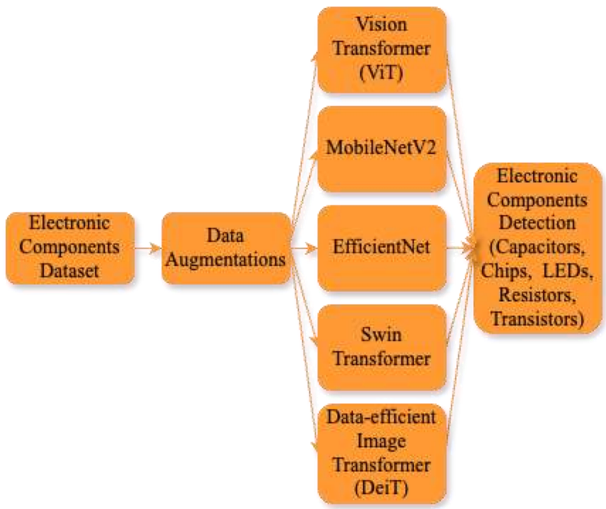

Figure 4. *Electronic components detection flowchart*

When figure 4 is analysed, it is seen that the open source electronic components dataset used in the study is not used in its raw form, but firstly it is subjected to data augmentation steps. After this step, multi-class classification processes were performed for the detection of electronic components with 3 different deep learning models based on Transformer and MobileNetV2 and EfficientNet deep learning models. For the deep learning models, the versions shared by Google, Facebook and Microsoft were used in the Image Classification task in the Models section of the Hugging Face platform [30]. The details of these models used are mentioned in detail in the subsections below.

3.1 Vision Transformer (ViT)

ViT deep learning model, which is frequently used in image classification problems, consists of Linear Projection of Flattened Patches, Transformer Encoder and MLP Head. There are three versions, ‘base, large, huge’, which differ depending on the number of layers and heads [31]. In this study, the ViT-base model, which has 12 layers and 12 heads and shared by Google on the Hugging Face platform, was used to detect electronic components.

3.2 MobileNetV2

MobileNetV2 deep learning model can be used in image classification, object detection and semantic segmentation problems. In this model, which includes Inverted residual blocks, there are also depthwise convolution layer and pointwise convolution layer [32]. The deep learning model used for this study in the detection of electronic components is the MobileNetV2 model shared by Google from the Hugging Face platform, as in the ViT model.

3.3 EfficientNet

In EfficientNet deep learning model, resolution, depth and width dimensions are scaled equally by using effective compound coefficient. This model, which uses compound scaling method, includes mobile inverted bottleneck MBConv [33]. This EfficientNet model, which is used for the electronic component detection process performed within the scope of this study, is the type of model shared through Google's Hugging Face platform.

3.4 Swin Transformer

Swin Transformer deep learning model is a model in which Shifted Windows is used unlike ViT model and can be used in image classification, semantic segmentation and object detection problems. The model basically includes Linear Embedding and Swin Transformer Block [34]. This type of deep learning model used in this study for the detection of electronic components is the Swin Transformer model shared by Microsoft from the Hugging Face platform.

3.5 Data-efficient Image Transformer (DeiT)

Data-efficient Image Transformer (DeiT) deep learning model is a model that can be used in image classification problems and can include Soft distillation, Hard-label distillation and Distillation token parts [35]. The model used for the electronic component detection process in this study is the DeiT model shared from Facebook's Hugging Face platform.

4. Results

Within the scope of the study, all necessary evaluation metrics including precision, recall, f1 score, accuracy and loss were obtained by using 5 different deep learning based models and multiclass classification processes in order to detect electronic components with 5 different classes. Precision (P.) value is equal to the ratio of true-positive (TP) value to the sum of itself and false-positive (FP) value and is given in equation 1. The Recall (R.) value is equal to the ratio of the sum of the TP value and the false-negative (FN) value and is given in equation 2. The calculation of the F1 score is equal to the ratio of twice the TP value and the sum of this value and the sum of the FP and FN values, and is given in equation 3. The Accuracy (Acc.) value is equal to the ratio of the sum of the true-negative (TN) value and the TP value to the sum of the TP, TN, FP and FN values and is given in equation 4.

$$\mathrm{P} = \mathrm{TP} / (\mathrm{TP} + \mathrm{FP}) \quad (1)$$

$$\mathrm{R} = \mathrm{TP} / (\mathrm{TP} + \mathrm{FN}) \quad (2)$$

$$\mathrm{F1} = 2\mathrm{TP} / (2\mathrm{TP} + \mathrm{FP} + \mathrm{FN}) \quad (3)$$

$$\mathrm{Acc} = (\mathrm{TP} + \mathrm{TN}) / (\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}) \quad (4)$$

As a result of the multiclass classification processes performed for the detection of electronic components, the results obtained using 5 different deep learning models, 3 of which are based on Transformer, are given in detail in table 1. According to table 1, it is observed that the results of ViT and Swin Transformer deep learning models,

Table 1. *Electronic components detection results*

Models	P.	R.	F1	Acc.	Loss
ViT	0.987	0.986	0.986	0.986	0.067
Mobile NetV2	0.757	0.744	0.735	0.744	0.806
Efficient Net	0.597	0.6	0.595	0.6	1.374
Swin T.	0.987	0.986	0.986	0.986	0.077
DeiT	0.992	0.992	0.991	0.992	0.040

which have a similar structure among Transformer models, are very close and approximately the same except for the loss results. In addition, when the loss values are analysed, it is understood that the lowest loss belongs to the DeiT model. Figure 5 shows a graphical comparison of the results of the precision, recall, f1 score and accuracy values of the deep learning models used in the study.

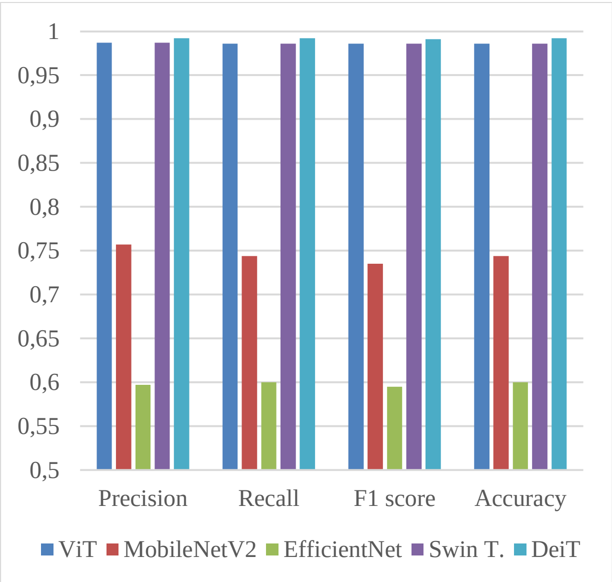

Figure 5. *Results of precision, recall, f1 score and accuracy*

When figure 5 is analysed in detail, it is observed that the highest precision, recall, f1 score and accuracy values are obtained in the DeiT model. Analyzing the results for electronic component detection, it is evident that the accuracy value obtained with the DeiT model, which yields the best classification result, is 0.992.

5. Conclusions and Future Works

Within the scope of the study, data augmentation steps were first performed on a 5-class and open-source dataset for the detection of electronic components. After these steps, 5 different deep learning-based models were used for multiclass classification operations. Upon examining the deep learning models for which accuracy values were obtained within the scope of this study, in which all necessary evaluation metrics were considered, it was observed that the models EfficientNet, MobileNetV2, Swin Transformer, ViT, and DeiT ranked from lowest to highest, respectively. A similar ranking is also available for precision, recall and f1 score values. As a result, considering all metrics, it is evident that the most suitable model for electronic component detection within the scope of this study is the DeiT model, a deep learning-based Transformer architecture. In addition to these 5 different classes of electronic components in future studies, other electronic components can also be added to the dataset. In addition to deep learning models for the detection of electronic components, classification studies can be carried out with machine learning models in future studies. Additionally, future research on electronic components can focus on various tasks such as classification, object detection, anomaly detection, and segmentation of printed circuit boards using AI.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** Data used in this study are available at https://www.kaggle.com/datasets/divyejoshi/pictures-of-simple-electronic-components (accessed on 1 October 2024).

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