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Research Article

Detection of circuit components on hand-drawn circuit images by using faster R-CNN method

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ABSTRACT

In this study, one of deep learning methods, which has been very popular in recent years, is employed for the detection and classification of circuit components in hand-drawn circuit images. Each circuit component located in different positions on the scanned images of hand-drawn circuits, which are frequently used in electrical and electronics engineering, is considered as a separate object. In order to detect the components on the circuit image, Faster Region Based Convolutional Neural Network (R-CNN) method is used instead of conventional methods. With the Faster R-CNN method, which has been developed in recent years to detect and classify objects, preprocessing on image data is minimized, and the feature extraction phase is done automatically. In the study, it is aimed to detect and classify four different circuit components in the scanned images of hand-drawn circuits with high accuracy by using the Python programming language on the Google Colab platform. The circuit components to be detected on the hand-drawn circuits are specified as resistor, inductor, capacitor, and voltage source. For the training of the model used, a data set was created by collecting 800 circuit images consisting of hand drawings of different people. For the detection of the components, the pretrained Faster R-CNN Inception V2 model was used after fine tuning and arrangements depending on the process requirements. The model was trained in 50000 epochs, and the success of the trained model has been tested on the circuits drawn in different styles on the paper. The trained model was able to detect circuit components quickly and with a high rate of performance. In addition, the loss graphics of the model were examined. The proposed method shows its efficiency by quickly detecting each of the 4 different circuit components on the image and classifying them with high performance.

1. Introduction

Each discipline may have its own terms and notations in which these terms are expressed visually. Especially in applied sciences, visuals where the terms correspond in real terms are needed. The figures of the terms are described by the way of drawings. The prevalence of drawings in many engineering fields shows that visuality is at the forefront. Drawings and visuality are also important in electrical and electronics engineering. Because in electrical and electronics engineering, a circuit diagram is drawn first, and then various analyses are made on it. This circuit diagram can be created by hand drawing or any drawing program. Although hand drawing is seen as a primitive method, it is generally the first preferred method. When an electrical and electronics engineer wants to design a circuit, initially the circuit components to be used in the circuit are decided. Then, a draft drawing is made on a paper by using the determined circuit components, and numerical values are assigned to each component. After this step, the mathematical calculations are made due to the aim of the circuit on the completed draft drawing. If the results are as expected, the circuit is set up for testing in a simulation program or in a real laboratory environment. However, it is time-consuming and tedious for engineers to redraw a hand-drawn circuit by using a circuit drawing program on the computer. Taking an image of the circuit drawn on the paper and transferring it directly to the simulation program through an interface or software provide a great advantage to engineers. In this way, the workload of the engineers is

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reduced, there is no need to draw the circuit on the computer again, and they save time. The creation of such a software and its success in the detection of the circuit components from the hand-drawn circuit images have great importance in the aspect of engineering science. Depending on the rapid advancement of science and technology, researchers tend to develop such applications that facilitate human life in recent years. Several applications based on different methods in the object detection and classification have made significant contributions to the literature on this subject. Also, there are many studies in the literature on this subject, which have become popular in recent years.

Some researchers have focused on the recognition and classification of hand-drawn circuits and circuit components, since great successes have been achieved in handwritten number recognition and handwritten character recognition studies in the literature. Machine learning-based and deep learning-based methods have been used in the studies on the detection and classification of hand-drawn circuits and circuit components.

For this purpose, the HOG method was used in the recognition of the components on the hand-drawn circuit, and the machine learning-based SVM and KNN methods were used in the classification of the circuit components. Liu and Xiao [1] first divided the hand-drawn circuit into sections using a topology-based segmentation method and then classified the components in the circuit with SVM. The classification success for each circuit component classified in the circuit was over 90%. Moetesum et al. [2] firstly applied segmentation and various preprocesses to the circuit to classify the circuit components on the hand-drawn circuit. After the segmentation process, they suggested using the histogram of directed gradient properties (HOG) method to detect the circuit components, and the SVM method to classify them. In the study, 10 different hand-drawn circuit components were classified, and the average classification success rate was 92%. Angadi and Naika [3] performed certain preprocesses on hand-drawn circuit diagrams with image processing techniques. They suggested using the SVM method in the classification stage, which is the decision-making stage in determining the hand-drawn circuit diagram. Dewangan and Dhole [4] achieved 90% success rate in the classification they made by using scanned images of 90 hand-drawn circuits using KNN method. Naika et al. [5] used the HOG method in the recognition of 10 different hand-drawn electronic components and the SVM method in the classification stage. In the study, a data set consisting of 2000 images was used. As a result of the study, the rate of success in recognizing electronic components was 96.9%.

With the rapid developments in the field of deep learning in recent years, many studies have been carried out by using deep learning-based methods. Deep learning-based methods have been used in hand-drawn electronic component recognition studies since the beginning of 2020. Wang et al. [6] used deep learning-based convolutional neural networks method to classify 3 different hand-drawn electronic components. The success rate of the method used in the study in classifying hand-drawn diode, resistor and capacitor images was stated as 90%. CNN, which is one of the deep learning-based methods, is generally used in the image classification [7]–[10]. The Faster R-CNN method, which was developed to determine the objects and the position of the objects on the images, is a new deep learning-based method. In the literature, there are many studies in which high performance was achieved by detecting objects using Faster R-CNN. Sardogan et al. [11], in their study, created a data set by collecting diseased and healthy apple leaf images. Using the Faster R-CNN method, they identified and classified the diseased and healthy leaves in the image. The proposed method achieved an average success rate of 84.5% in this study. Cömert et al. [12] first prepared a dataset containing 1200 apple images. After the training phase was completed with the images in the dataset, they detected the rotten area on the apple using the Faster R-CNN method. As a result of the study, they achieved an average of 84.5% success. Ren et al. [13] made some changes and adjustments in the Faster R-CNN method and used it for object detection in optical remote sensing images. Julca-Aguilar and Hirata [14] suggested using the Faster R-CNN method to detect symbols found in handwritten graphics and mathematical expressions. Yang et al. [15] conducted an experimental study using the Faster R-CNN method in handwritten text recognition studies. As a result of the study, they stated that the average success rate of the method used in character recognition was 97%.

In this article, the Faster R-CNN method, which is a deep learning-based object detection method, is proposed for the detection of circuit components in a hand-drawn circuit image. A data set was created by collecting the hand-drawn circuit images. After the labeling processes in the data set were completed, the pretrained Faster R-CNN model was selected. The training process was carried out using the selected model. Finally, the model is tested on various hand-drawn test circuits and the resulting loss plots are evaluated.

The main contributions of this study can be expressed as follows: It is demonstrated that basic circuit components, which are hand-drawn by different people, can be classified with a great accuracy by using Faster R-CNN method. Also, it is shown that this method is quite useful for the applications, where object detection and high speed is needed.

2. Material and Method

2.1 Data set

As the first step of the study, a data set including 800 hand-drawn circuits has been prepared. In this kind of studies, the data set is generally created in two ways. The first way is to use a ready-prepared data set that can be found on various web platforms. The second way is to use a data set created by the participants of a specific study. Since this study is about the hand-drawn circuit images and it is difficult to find an available data set intended for such a study, a data set specific to this study was created with the scanned images of circuits drawn by different people manually. The circuits were drawn on a white A4 paper by many people in different styles. Scanned images of 800 hand-drawn circuits were collected to create a data set to be used in the study. Since the scanned images were of high size, first the images were resized and reduced. 80% of the collected 800 images was reserved for training while the remaining 20% was reserved for validation.

Four different components have been defined to be detected in the hand-drawn circuit images. These are voltage source, resistor, inductor, and capacitor. Figure 1 contains sample images from the circuit components in the dataset.

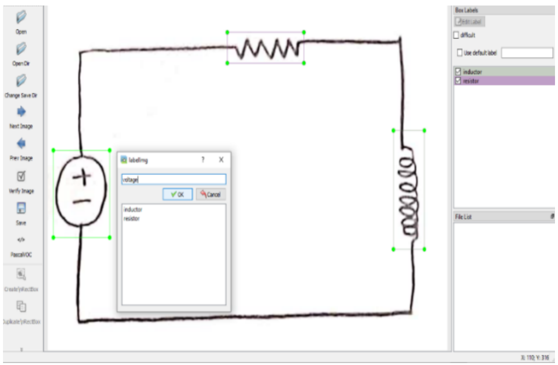

Figure 1. Sample images of the classes in the dataset

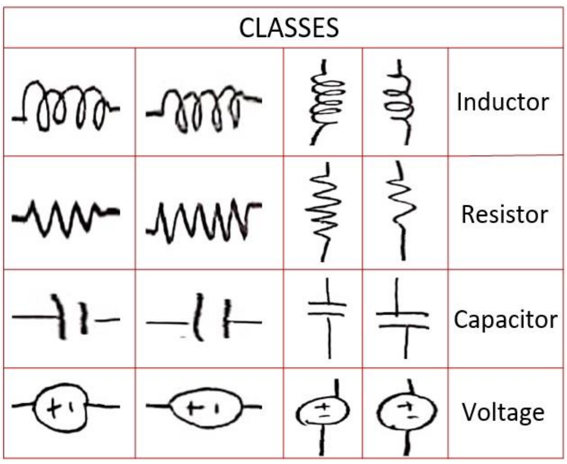

Figure 2. Sample images of the classes in the dataset

Since the aim of the study is to determine the circuit components on the images, different from the classification studies, the location of each circuit component is needed. For this reason, the circuit components on the images in the data set are labeled using the LabelImg program which is a graphical image annotation tool written in Python [16]. Figure 2 shows the labeling process of all the components in the images in the dataset with the LabelImg program.

2.2 Deep Learning and Convolutional Neural Networks

Deep learning is a newer field than artificial intelligence and machine learning. Unlike classical learning methods, deep learning is closer to the human brain because it consists of multi-layered neural networks [17], [18]. Since human is the creature in the nature that is the best at learning and applying the knowledge, the recent studies focus on developing novel learning algorithms similar to ones used by human brain. Considering the mentioned reasons, the deep learning method is frequently preferred for the studies on object detection and image processing by the researchers. Due to the widespread use of deep learning in different areas, various deep learning models specific to the field have been developed. Each of the developed models differs from each other and is used to solve problems in different areas. It is a great advantage to use deep learning approaches in classifying the images according to the categories and detecting the objects on the image, since it has high performance feature extraction ability.

At the beginning of 2012, the convolutional neural network architecture, which is a useful deep learning model in visual recognition, has been developed to use in specific fields. CNN architectures are mostly preferred in the education and classification stages of image processing studies. A basic CNN model is usually designed by using convolution layer, activation function, relu layer, pooling layer and fully connected layers [19]. For classification in the CNN model, a classification layer selected by the user is added to the backside of the fully connected layer. The number of layers to be used may differ depending on the model to be applied. There are many CNN-based ready-made models used in several studies, and these models differ according to the parameters such as the number of layers used, the order of the layers, and the learning rate. In addition, some users have designed their own CNN models instead of using ready-made models to use in their own studies. The main reasons for the increase in CNN usage in many different areas can be explained as follows: It is easy to apply, fast in training and testing stages and has efficient feature extraction stages occurring automatically through layers.

3. Proposed Faster R-CNN Method

The CNN algorithm estimates the class of a given image and yields as an output [20]. It is possible also to estimate the class of the object on an image using CNN. However, it is not possible to find the position of the object on the image by using CNN. For this purpose, a new model called R-CNN, which is one of the deep learning methods based on CNN, has been created to solve the object detection problem on the image [21]. In the R-CNN method, firstly, 2000 different regions are suggested with the selective search algorithm on the image. All proposed regions are transferred to the CNN model named Convnet, and feature map of each region is drawn. SVM method is used to classify by considering the extracted features. Finally, a bounding box plot is required to indicate the location of the object, and a regression model is used for this purpose. In the R-CNN method, training is completed in approximately 84 hours. The estimated time for a single image is about 47 seconds. In the R-CNN method, the training is slow and takes a long time, since CNN is applied for all the proposed regions. The scientists, who designed the R-CNN model, realized the disadvantages of R-CNN model and created a new model called Fast R-CNN [22]. While creating Fast R-CNN, some changes were made in R-CNN. In Fast R-CNN, unlike R-CNN, after CNN is applied to the image, 200 different regions are suggested by using the selective search algorithm. The ROI is then passed through the pooling layer to ensure the images are equal in size. Finally, the Softmax classifier is used to classify the desired objects. In the Fast R-CNN method, the training is completed in approximately 8.75 hours. The estimated time for a single image is 2.3 seconds. When the Fast R-CNN and R-CNN methods are compared, it has been stated in the literature that the speed performance of Fast R-CNN is better than R-CNN. As a result of the changes made to increase and speed up the performance of the Fast R-CNN model in 2017, a new model named Faster R-CNN was proposed [23]. In this method, CNN is applied to the image in the first step, as in Fast R-CNN. In the second step, the selective search algorithm is used. Thanks to the RPN algorithm used, the zone proposition phase has been accelerated. Thanks to the Faster R-CNN method, it has become possible to detect the objects on the image in a fast way with high-performance. The application steps of Faster R-CNN method are shown in Figure 3 with block diagrams [24], [25]. In this article, Inception V2 model [26], one of the pretrained Faster R-CNN models, has been preferred to detect circuit components on hand-drawn circuits.

As seen in Figure 3, after the model is selected, CNN is applied to extract the feature map of the input image. RPN is used for region propositions using extracted feature maps. Features and proposed regions are passed through the ROI pooling layer. Features and suggested regions at the exit of the ROI pooling layer will be the same size. Then, a bounding box is drawn around the object on the image at the output and the class of the object is estimated by using the Softmax function.

In the Faster R-CNN method, the number of preprocessing steps on the images is small compared to other object detection and machine learning methods that are available in the literature. The preprocessing steps are few in this method, the method is realized successfully and quickly despite the high-level features of the image to be processed.

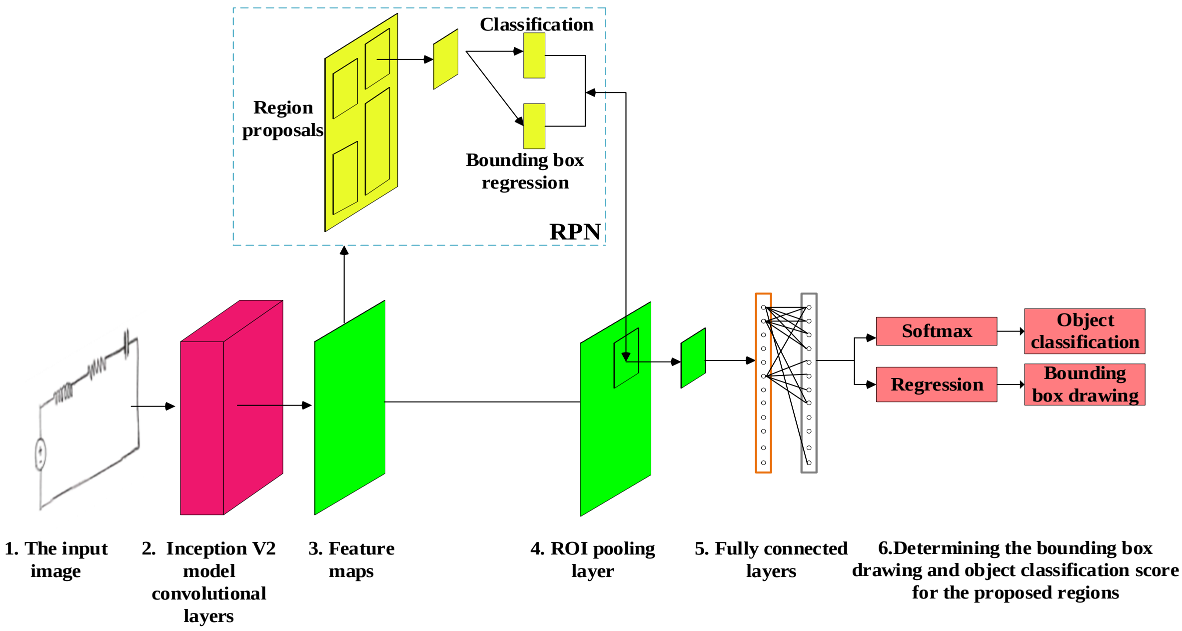

Figure 3. Representation of Faster R-CNN architecture

4. Experimental Results

In this study, a certain way has been followed to detect and classify circuit components found in hand-drawn circuit images. The steps followed in the study are shown in Figure 4.

Before using the pretrained Inception V2 model, the data set was created as a first step. After creating the data set, certain preprocesses were applied. All the images in the data set were resized as 200 * 200 pixels, and all images were brought to the same size. Within the composed data set, two separate files were created for training and testing. 80% of the images in the data set were transferred to the train folder and the remaining 20% to the test folder. Then all the images in the data set were labeled. An xml file was created for each image in the train and test folder. The xml file contained the class information and coordinate information of the objects. All xml files in train and test folder were converted into a single csv file. After the preliminary preparations for the application were completed, Google Colab [27] cloud environment was preferred to use the Faster R-CNN model. The application of the proposed hand-drawn circuit component detection system was realized after necessary adjustments and arrangements were made on the Inception V2 model, which was pretrained by using Python software language. NVDIA Tesla K80 GPU, offered free of charge by Google Colab, was used as the graphics card.

The model has been trained in 50000 epochs. The positions of the circuit components on the hand-drawn circuits having different styles can vary in each image. Also, depending on the purpose of the circuit, these four components may not be present in each circuit. Because each designed circuit and each component in the circuit has a task to perform. Considering the situation of the circuit components in different positions on the circuit, the trained model was analyzed on various hand-drawn circuits. Figure 5 shows the real-time detection of circuit components on 4 different hand-drawn circuit images. As seen in Figure 5, the trained model has identified the components on the circuits by drawing a rectangular frame with different color tones. In addition, the model made an estimation in percent ratio for the label of the component detected with each rectangular frame drawn.

Loss functions were examined in the study to evaluate the performance of the trained Faster R-CNN Inception V2 model in detecting the components on hand-drawn circuits. In loss function graphs, the lower the loss means the higher the accuracy rate of the model. Therefore, when evaluating the success of the model, the loss is expected to decrease gradually as the number of epochs increases.

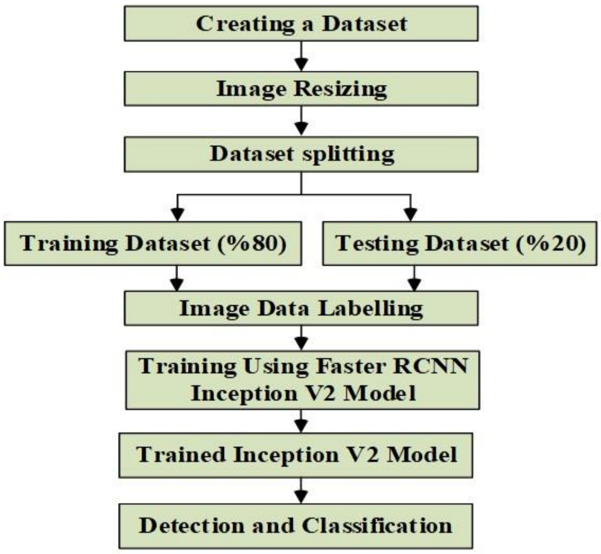

Figure 4. The steps followed to detect the circuit components in hand-drawn circuits

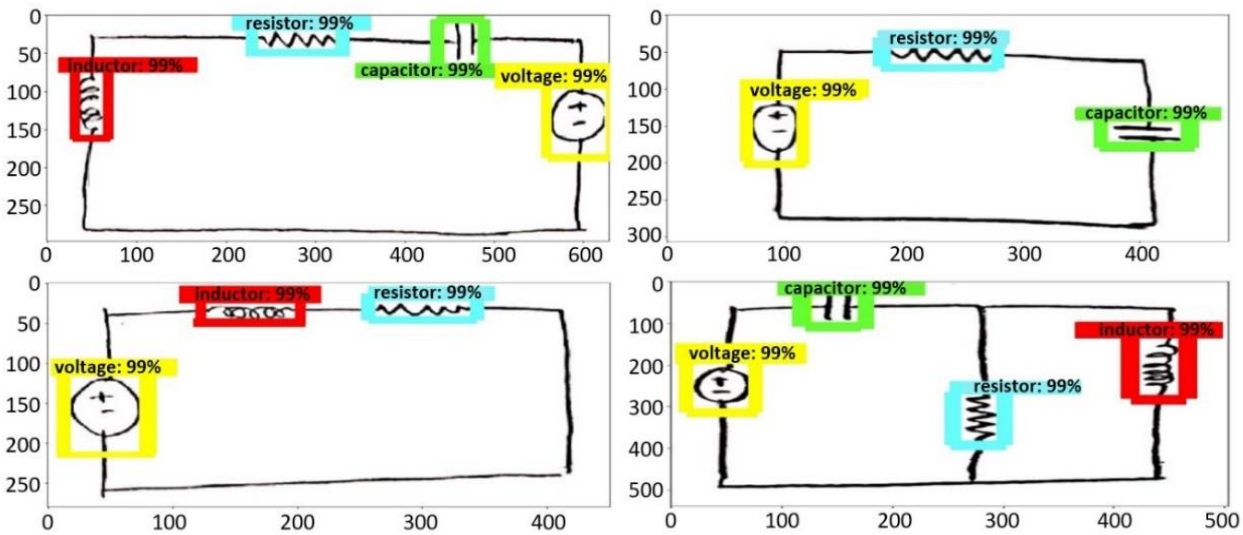

Figure 5. Real-time detection of components in the different circuit images tested

In Figure 6, various loss functions of the model that detect the components in the 50000 epoch trained hand-drawn circuit are given. The total loss function of the model is given in Figure 6 (a). The total loss function shows the overall loss of the model. When Figure 6 (a) is examined, the total loss has decreased to 0.06 at the end of 50,000 epochs. The classification loss function of the model is given in Figure 6 (b). The classification loss function shows the loss of the model at the classification stage. When Figure 6 (b) is examined, the loss in classification has decreased to 0.03 at the end of 50000 epochs.

In Figure 6 (c), the loss function of the model to determine the positions of the circuit components is given. As seen in Figure 6 (c), at the end of 50000 epochs, the localization loss has decreased to 0.02. When the loss graphs showing the performance of the model are examined, a gradual decrease in the loss is observed and after a while the loss started to remain constant. Considering the total loss graph, the model loss was a minimum of 0.048. As the number of epochs increased, the loss of model gradually decreased to less than 0.1. This shows that the model will have a high accuracy rate in real-time detections.

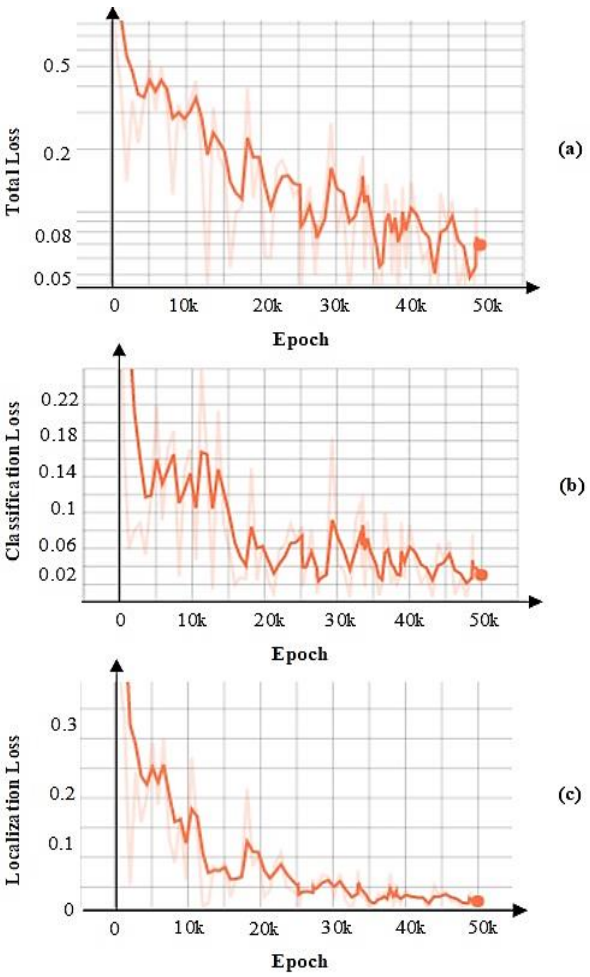

Figure 6. Loss function graphics for a) Total loss, b) Classification loss, c) Localization loss

5. Conclusions

In this study, the Faster R-CNN object detection method is used to detect circuit components from various hand-drawn circuit images. A lot of image data is needed to train the Faster R-CNN architecture, which is a deep learning model. In the study, the Inception V2 Faster R-CNN architecture, which was pretrained with a hand-drawn circuit data set and has a high success rate, was employed for object detection and classification. For this purpose, the necessary settings and arrangements were made by choosing a pretrained model in the study. Then, the model was trained with the data set created for the study with the images of 800 circuits drawn in several styles by many different people. The trained Faster R-CNN model has been applied, and the results were analyzed for many hand-drawn circuits where circuit components are designed in different positions. Softmax was preferred as the classification function. According to the results obtained, it has been observed that the method used has a high success rate in the detection of hand-drawn circuit components both in series and parallel RLC circuits. In the next studies, it will be focused on the detection of these components separately in hand-drawn circuits created by using semiconductor circuit components together with passive circuit components. In the next stage, it is planned to take photos of the circuits drawn on paper and transfer them to simulation programs such as Pspice, Proteus and Multisim through an interface to be developed.

Declaration

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The authors also declared that this article is original, was prepared in accordance with international publication and research ethics, and ethical committee permission or any special permission is not required.

Author Contributions

M. Günay collected the data and conducted the experiments based on the mentioned methodology. All the authors contributed to the analysis and writing phases. M. Köseoğlu supervised the work and provided some improvements. The work has been derived from M. Günay’s ongoing master thesis, and M. Köseoğlu is the thesis supervisor.

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