Real-Time Seven Segment Display Detection and Recognition Online System Using CNN

Autanan Wannachai, Wanarut Boonyung, and Paskorn Champrasert(✉)

OASYS (Optimization Applications and Theory for Engineering SYStems) Research Group, Faculty of Engineering, Chiang Mai University, Chiang Mai, Thailand
autanan.wan@gmail.com, wannarut.b@gmail.com, paskorn@eng.cmu.ac.th

Abstract. Typically, manufacturing machines represent their working status via the seven-segment LED display. The operators have to read the machine working status periodically. The process information time-lagging and human-error may occur. These causes may defect the output products and reduce manufacturing productivity. This research paper proposes a real-time and automatic machine display tracking system. The proposed real-time seven-segment LED display recognition system is designed to apply to the actual machines in the manufacturing. However, the camera installation problem degrades the image qualities such as machine vibration, light reflection, brightness, and camera view's frame changes. The proposed **R**eal-time **S**evens segment **D**isplay detection and recognition online system using **C**NN (RSDC) consists of the camera controller module and the **I**nterpretation of **S**even-**S**egment display (ISS) framework. The RSDC can track the machine's display and interpret the camera images to numerical data using the machine learning technique to handle the installation problems. The experiment result shows that the proposed ISS framework has an interpretation accuracy of 91.1%.

Keywords: Seven-Segment Display Detection · Seven-segment recognition · Convolution Neural Network · Detection · Recognition

1 Introduction Section

Generally, manufacturing machines show their working status as numerical data using the seven-segment LED displays. The operators have to visually track the machine working status from the LED displays. However, in an actual situation, the operators cannot monitor the machine all the time. The process information time-lagging and human-error may occur [1, 2]. The machine failure detection is delayed. The produced goods may have defected. The apparent method to solve this problem is to apply the real-time automatic monitoring system to the machine. However, because of the machine guarantee contract and the complicated machine modules, the machine cannot be modified by local mechanics.

Y. Chen et al. (Eds.): BICT 2020, LNICST 329, pp. 52–67, 2020.
https://doi.org/10.1007/978-3-030-57115-3_5

To automatically obtain the working machine status without the machine's modification, image recognition techniques are widely applied in researches [1, 3, 4]. A digital camera is installed to the manufacturing machine to capture the seven-segment display image. Then, the images are analyzed and transformed into numerical data using image processing algorithms. The image is preprocessed to crop the desired area and reduce the image noise. A recognition technique is applied to identify each digit's position and numerical data interpretation. However, challenges are dealing in this process. The challenges include background color separation, floating character position finding, light disturbance elimination, and image sharpening). These challenges affect the quality of the detection result [7, 8]. Moreover, the manufacturing environmental condition variation becomes the great impact on the image processing algorithm accuracy. There are different kinds of machines, the camera module cannot be installed at the same position in all machines, the view's frames are different. Finding the edge of the display screen automatically becomes a challenge in this case.

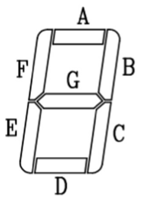
In this research, the **R**eal-time **S**even-segment display **D**etection and recognition online system using **C**NN, named **RSDC**, is presented. The RSDC is designed to automatically track the numerical data from the seven-segment displays of the manufacturing machines. The RSDC consists of the camera module and the **I**nterpretation of **S**even-**S**egment display framework (ISS framework). The ISS framework applies the Convolution Neural Network (CNN) for seven-segment display detection and recognition. The Convolutional Neural Network (CNN) is inspired by the human neural network, a biological inspired algorithm, to applies identical copies of the same neuron and express the recognized patterns without having to re-learn the concept [14].

The RSDC is also designed with practicality and simplicity concept. The camera modules have been installed in the actual manufacturing site for three months. The camera modules take pictures of the seven-segment displays. The image files are transmitted and stored in the remote server. Then, the remote server processes the image files using the ISS framework. The numerical data output can be visually represented on the graphical information in a real-time manner.

This paper is organized as follows. Section 2 describes the machinery display technique. Section 3 shows the system design. Section 4 shows the experimental results. The conclusion is discussed in Sect. 5.

2 The Machinery Display Technique

In manufacturing, the machines show the data and their working status through a simple display [1–3]. There are two types of the seven-segment display, which are LCD (Liquid Crystal Display) and LED (Light Emitting Diode) seven-segment. Both types of screens are used to display the numerical data of the machine working status. The seven-segment format is a combination of seven LEDs (or liquid crystal display). The seven LEDs assemble to create the number according to the position A–G, as shown in Fig. 1(a), which called the LED seven-segment one digit. The seven-segment LED one digit represents one number of data. The seven-segment display can be concatenated to represent a set of number digits (i.e., numerical data). Figure 1(b) shows an example of the LED seven-segment display.



(a)

(b)

Fig. 1. (a) The seven-segment format, (b) LED seven-segment display.

The machines are usually designed to display the working status in an offline manner to reduce the cost and hardware complexity. To access the working status, an operator needs to access the machine manually [1, 2, 5, 6]. In this case, data collecting by the operator cannot be in a real-time manner because the operator cannot keep watching the machine display and record the data all the time. When there is a problem with the machine, the corrective actions may not occur immediately. The lack of real-time data causes the job or product to be delayed and fails in the working process.

To track the status of the machine, the camera, and image processing method for accessing the working machine status is presented in research works [11, 12]. This method, the camera module is not required to contact any parts of the machine. The camera is responsible for capturing and storing the picture to the server. The image files in the server are processed to numerical data using the image processing algorithm. This process is called the detection and recognition process. The detection and recognition process has two steps which are 1) finding of the display location in the image file (i.e., detection step) and 2) interpretation of the image to the numerical characters (i.e., recognition step).

The detection step is to locate the seven-segment display within the image. There are many ways to detect the seven-segment display, such as determining the exact position of the display from the image [4], indicating the specific color of the background [8], and separating the color and brightness [7]. The result from this detection step is the image that is cropped out the background from the seven-segment display. After that, the detection step reduces the noise in the image with the filter, rotates the image with the degree of the edge detection area.

The recognition step is to identify the position of a number and specify the value of the number. There are many ways to identify the position and value of numbers, such as feature extraction of the numerical data [11], counting the pixels density in each part of the image [8], and using machine learning techniques for number interpretation [9, 10]. The result of the recognition step is the value one digit number. Each number is arranged to calculate the numerical data value.

However, the detection and recognition process face with several challenges in the actual environmental conditions. The example pictures of the captured display screen are represented in Fig. 2. The capture images are a skew image, a light disturbances image, a blurry image, and an intricate background image. These four images are taken from the same camera module at the different times. The actual environmental condition

Fig. 2. Difficulties in the detection and recognition process (skew image, light disturbances image, blurry image, and intricate background image).

installation brings the difficulties to the detection and recognition process without a machine learning mechanism.

In [7], the authors proposed a framework for the seven-segment display detection and recognition method. The framework applies a predefined HSV color slicing technique. This technique is used to separate parts of a number's position from the background by specifying the color and light of the number. This technique returns high accuracy. However, the HSV color slicing technique applies many parameters in the detection and recognition process. The detection process needs to set the HSV parameters, such as Hue (H), Saturation (S), and Value (V) of character colors. Those parameters affect the performance of the accuracy of the detection process. The hue, saturation, and character color value settings also lead to the wrong location of the display screen finding. In this case, the low accuracy of position detection leads to the very low accuracy in the recognition process too.

In [8], the authors proposed a recognition process based on the pixel density feature extracting method. This process is to compare the characteristics of numbers by the pixel density. The number display will be divided into many parts. Each part has a different density of pixels. The different numbers result in a different pixel density of each part. The recognition process can compare the pixel density of each part with the predicted number. This method returns a good accuracy, about 80%, in the numerical recognition. However, this method is major affected by the brightness and the light reflections on the display.

Thus, this paper proposes to apply a machine learning mechanism in the detection and recognition process to tolerate with the environmental condition changes. The simple convolution neural network (CNN), inspired by the human neural networks, is applied in the recognition step in the proposed **I**nterpretation of **S**even-**S**egment display framework, ISS framework. In the detection step, the encoder-decoder process, noise-canceling, and image transformation are also applied. The proposed ISS framework method is designed to return the high accuracy of numerical data interpretation against the environmental condition changes.

3 System Design

The **R**eal-time **S**even Segment **D**isplay Detection and online Recognition using **C**NN system, RSDC system, is proposed. The RSDC system is designed to automatically track the seven-segment display of the manufacturing machine. There are two parts of the RSDC system 1) the camera control module to take pictures of a seven-segment display at the machine and 2) the **I**nterpretation of **S**even-**S**egment display framework, ISS framework to invoke the detection and recognition process. The captured images from the camera control module are transmitted to the remote server through the wireless communication. Then, the remote server processes each image and stores it into the database. Periodically, the image is processed through the noise filtering process. The post-processed numerical data is shown on the online website. Figure 3 shows an overview of the RSDC system.

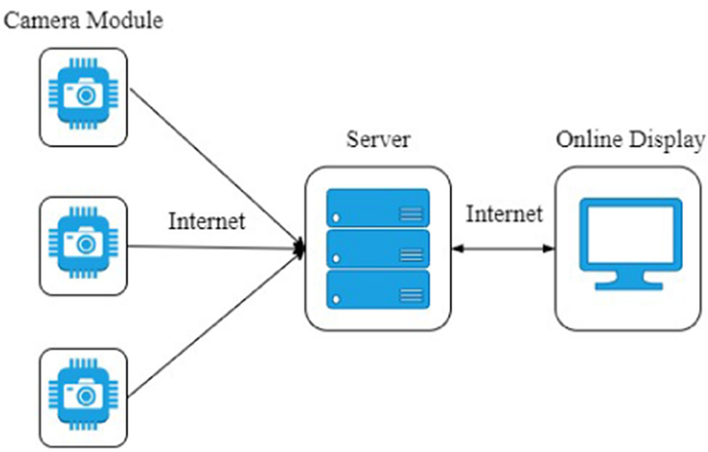


Fig. 3. The **R**eal-time **S**even-segment **D**isplay Detection and online recognition using **C**NN System (RSDC System)

3.1 Camera Control Module

The raspberry pi is the main controller in the camera control model. The camera control module takes pictures and transmits the image files to the remote server. The raspberry pi, as a main controller, is connected to the camera, control switches, and status LEDs. When the camera control module successfully connects to the remote server, its LED connection status will be turned on. In the case then the module cannot communicate with the remote server, the captured image files will be stored in the local storage. The error LED status will show up. The raspberry pi used in this RSDC system is the 4th model, the ram size is 8 Gb, the 32 GB SD card is used to store system data, image files, and program code. The camera used is a Logitech webcam 270. The power supply is a 5 V, 3 Am. AC to DC adapter, as shown in Fig. 4. The image capture frequency and other configurations can be adjusted by changing the parameters in the program code.

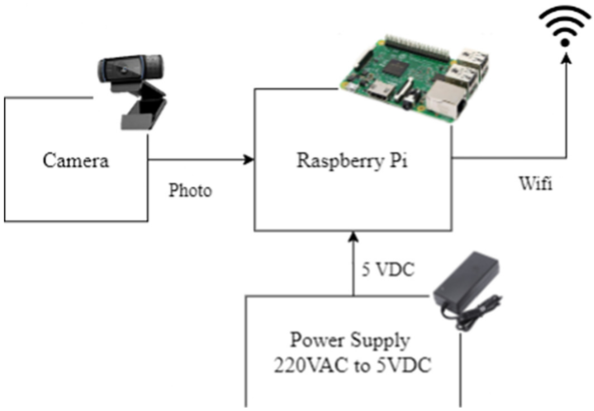


Fig. 4. The camera control module

3.2 Interpretation of Seven-Segment Display Framework

The proposed Interpretation of Seven-Segment display framework is divided into three procedures which are 1) Seven-Segment Display Detection (SSDD) procedure, 2) Seven-Segment Display Recognition (SSDR) procedure, and 3) Post-Processing procedure. Figure 5 shows an image of the ISS framework. The captured image is imported to the SSDD procedure, in which the SSDD procedure consists of four steps: 1) seven-segment display segmentation, 2) noise-canceling in segmentation, 3) merging segmentation and finding minimum rectangle, and 4) image transformation. After the SSDD processed, the output image will be cropped to only the seven-segment display image. Next step, the output image is imported into the SSDR procedure. The SSDR procedure will identify the number of an image. The SSDR procedure consists of digit scanning and number defining. The post-processing procedure consists of cutting noise and filtering.

A. Seven-Segment Display Detection (SSDD)

The seven-segment display detection procedure proposes a robust machine display detection. Mostly, the captured images contain unclear background, noise, and light reflections. This seven-segment display image is shown in Fig. 6(a). This procedure can detect and crop only the machine display, which could be achieved as follows:

1) Seven-Segment Display Segmentation

The seven-segment display segmentation procedure uses Convolution Neural Network (CNN) technique. The CNN is an artificial neural network which is one of the bio-inspired algorithms. The CNN imitates the machine's vision as the human's vision. The human sees the image as sub-areas. They combine the group of sub-areas to determine what they are seeing. This paper proposes the CNN technique to make the machine learn where the position of the number display in the image.

CNN's structure uses the encoder-decoder model. This paper proposes the CNN four convolution layers encoder and four convolution layers decoder model. The convolution layers of encoder consist of 16 nodes, 32 nodes, 64 nodes, and 128 nodes, respectively. Adjacent encoder layers use a down-sampling layer with pooling size 2 × 2 pixels for

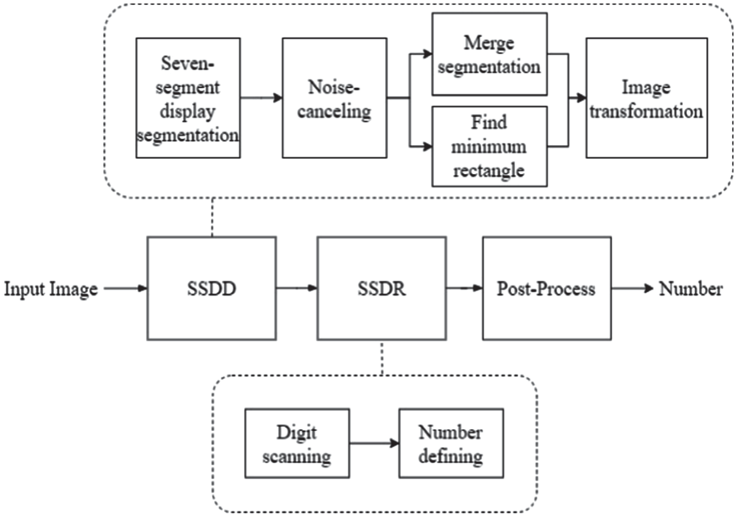


Fig. 5. The block diagram of the ISS framework

reducing the complexity. All encoder layers use Rectified Linear Unit (ReLU) activation function. The convolution layers of decoder consist of 128 nodes, 64 nodes, 32 nodes, and 16 nodes, respectively. Adjacent decoder layers use an up-sampling layer with size 2×2 pixels for increasing the resolution. All decoder layers use the Rectified Linear Unit (ReLU) activation function.

The Encoder's input is the captured image. The input image contains red, green, and blue color pixels in 2 dimensions matrix. The resized image is shown in Fig. 6(b). The encoder encrypts the input image to many feature maps output. The feature map is the description value of input data. This segmented image is shown in Fig. 7(a).

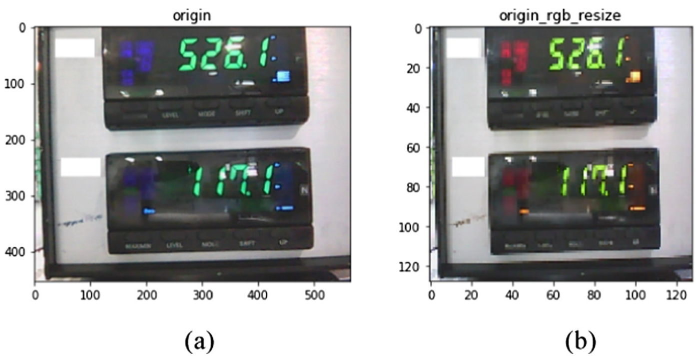
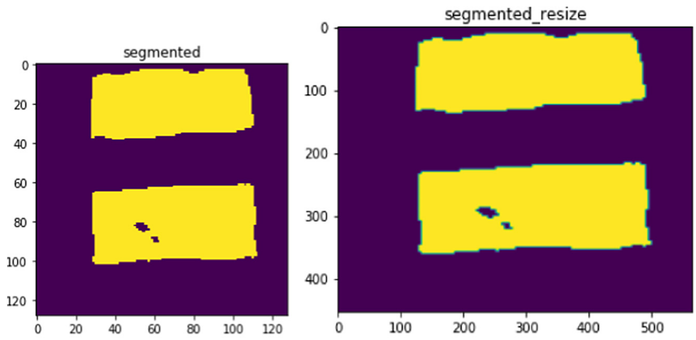


Fig. 6. (a) The BGR color input image, (b) The resized RGB input image (Color figure online)

The decoder's input is the feature map from encoder output. The decoder decrypts the feature map to be an output image. The output layer uses the sigmoid activation function.

The output image of this process is a binary segmented image of the seven-segment display.



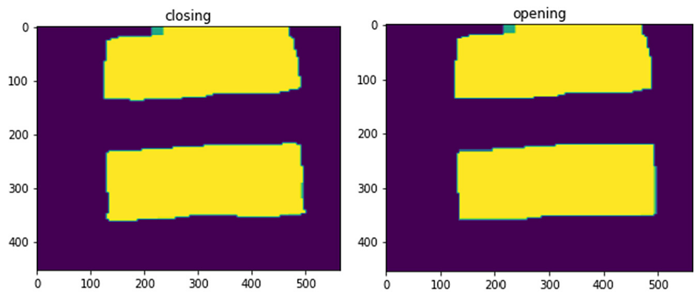
(a) (b)

Fig. 7. (a) The segmented image (b) The resized segmented image

2) Noise-Cancelling

The noise-canceling procedure uses a morphological operator technique. This paper proposes two steps in this process. The noise-canceling process input is the resized segmented image, as shown in Fig. 7(b). In the first step, the system fills the holes in a segmented image. This step uses the closing morphological operator method with structuring element size 30 $\times$ 70 pixels. The resulting image of this step shown in Fig. 8(a).

In the second step, the system removes the noise spots in the segmented image. This step uses the opening morphological operator method with structuring element size 50 $\times$ 100 pixels. The resulting image of this step is shown in Fig. 8(b).



(a) (b)

Fig. 8. (a) The closing segmented image (b) The opening segmented image

Then, this process applies the grayscale color threshold to filter the segmented image. The grayscale color threshold value varies between 50 and 255. This process output is the cleaned segmented image to be applied in the next image processing procedure.

3) Merging of Segmentation and Finding of the Minimum Rectangle

The merging of segmentation and finding of the minimum rectangle are the two parallel processes. First, the segmentation merging process uses an and-bitwise operation. This process merges the input image and segmented image to remove irrelevant information. The segmentation merging process output is only the machine display image. The output image of this step is shown in Fig. 9(a) (Fig. 10).

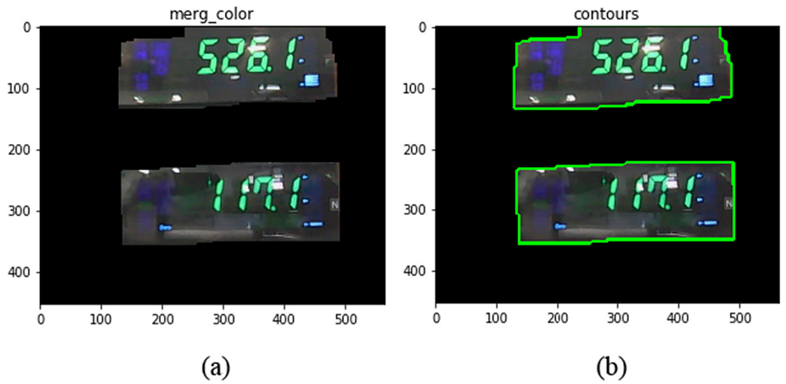


Fig. 9. (a) The merged segment image (b) The edge of a machine display image

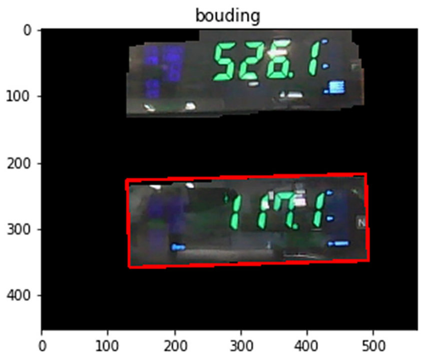


Fig. 10. The rotated rectangle.

Then, the minimum rectangle finding process is applied to find the rotated rectangle of the minimum area. This rectangle can enclose the machine display, as shown in Fig. 9. This rectangle found by the edge of a machine display image. The edge of a machine display is shown in Fig. 9(b).

4) Image Transformation

The image transformation procedure applies rotation and cropping process based on a rectangle image. This rectangle comes from the previous minimum rectangle finding procedure. The rectangle consists of the angle value. This rectangle is angled to the horizontal plane equal that angle value. This process rotates the machine display to the horizontal plane for a comfortable cropping image. The resulting image of this step is shown in Fig. 11(a). Then, cropping process is applied to the rotated image by using the image slicing technique. The image slicing technique is an element extraction method. The image transformation process output is a full horizontal machine display image. The resulting image of this step shown in Fig. 11(b).

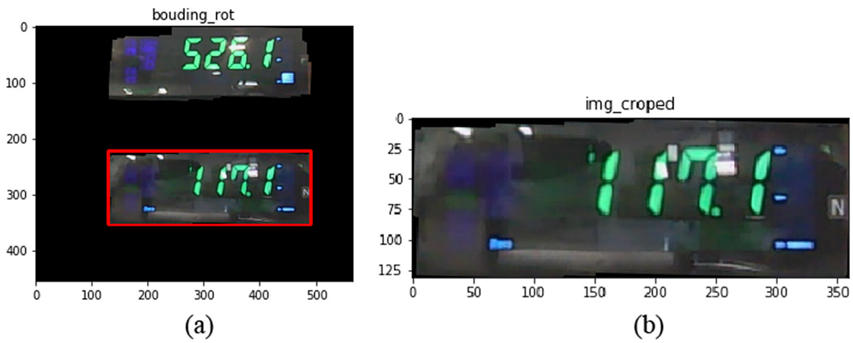


Fig. 11. (a) rotated display image (b) full horizontal machine display

B. Seven-Segment Display Recognition (SSDR)

The seven-segment display recognition procedure proposes a high precision CNN model for machine display recognition. This paper applies the CNN model to be a descriptor because it requires few amount of setting parameters compared to other techniques (e.g., Histogram of Oriented Gradients (HOG) and Hue (H), Saturation (S), and Value (V) of character color threshold method). This process can be applied as seven-segment. The steps are applied as follows:

1) Digit Scanning

The digit scanning step uses a color threshold, rectangle ratio, and stride image slicing technique. In the first step, the color threshold technique can filter only expected to be a seven-segment area. This step uses the blue, green, and red (BGR) color threshold values between (20,150,20), and (230,255,230), respectively.

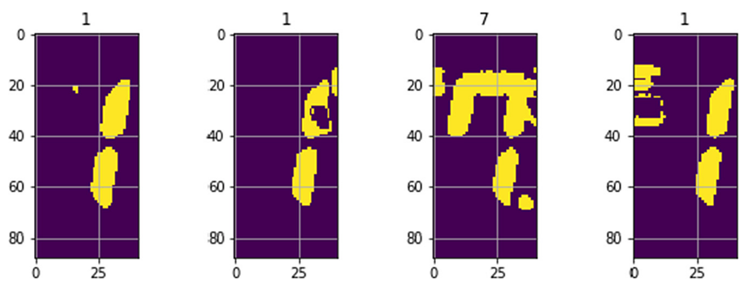


Fig. 12. The output of the digit scanning process.

In the second step, the rectangle ratio technique uses the width and height of the rectangle to calculate the relative rectangle of a digit. The rectangle ratio consists of the width ratio and height ratio. This paper uses the width ratio, and heights ratio is 8.6 and 1.5, respectively.

In the third step, the stride image slicing technique uses a sequential image slicing technique. The sequential image slicing is cropped based on the relative rectangle of a digit start at the right-hand side to the left-hand side. The resulting image of this step shown in Fig. 12.

In the last step, the process calculates the summation value of a digit image. If this summation value more than 30,000, then the digit image is expected to be the seven-segment area. The expected to be the seven-segment area cropped for training the recognition model in the number defining process.

2) Number Defining

The number defining process uses Convolution Neural Network (CNN) technique. This CNN's structure uses the simple CNN. This paper proposes the CNN 2 convolution layers as feature extraction and one fully connected layer as a classification model. The feature extraction is the description of the input data attribute. The classification is the decision method from using many feature extractions.

The simple CNN input is expected to be the seven-segment area. The expected to be the seven-segment area is black and white color value in two dimensions matrix. The number defining process output is number.

C. Post Processing

The post-processing is designed to improve the accuracy of the numerical data identification. The numbers that are output from the SSDR procedure are filtered with the **A**daptive **B**ound **C**riteria method (ABC) [13]. Noise data will be cut in real-time from the output number set. The **ABC** method is a mechanism to find the value boundaries based on data changes. The ABC method consists of 4 steps as follows: Trend lines creation, Bound size creation, Upper-Lower bound creation. The trendline creation is shown in Eq. 1, α is an EWMA constant number between 0 and 1. C_t and C_{t-1} are the trendlines at the time t and time $t-1$, respectively.

$$C_t = (1 - \alpha)C_{t-1} + \alpha D_t \tag{1}$$

$$\beta_t = (1 - \lambda)\beta_{t-1} + \lambda \delta_t \tag{2}$$

Equation 2. shows the creation of the bound size (β_t). λ is a constant number between 0 and 1. Delta (δ) is the difference between the current data (D_t) and previous data (D_{t-1})

$$U_t = C_t + \beta_t \tag{3}$$

$$L_t = C_t - \beta_t \tag{4}$$

The upper-lower bound creation is shown in Eq. 3, 4. U_t is the upper bound threshold. L_t is the lower bound threshold. When the number at the current time is in the range of the upper-lower bound, the number will use that number. If the number goes out of the upper-lower bound, that number will be replaced by the number from the trend-line.

4 Experiment and Result

This session evaluates how the RSDC system can perform to track the numerical data from the real-time seven-segment display of manufacturing machines. The proposed algorithm, ISS framework, has been evaluated with 200 real-time images. The images are captured and stored in the remote server every 30 s. The experiment is conducted through a set of simulations to evaluate the ISS framework in terms of accuracy. Section 4.1 provides the parameter setup and simulation configuration. Section 4.2 discusses the accuracy results of the ISS framework.

4.1 Parameter Setup

This section is an experiment to adjust the number defining process parameters in the seven-segment display recognition procedure. This paper proposes a high precision CCN model for recognition. Table 1 shows the CNN parameter setup. The number of nodes in the first and second convolution layers of feature extraction starts at two nodes and doubly increases. These convolution layers can isolate adjust the number of nodes. The number of nodes in a fully connected layer of classification are 16 nodes. The number of nodes affects the complex feature extraction and classification in the next layer. The number of output layers is the confidence value of seven-segment recognition. The confidence value is eleven values (0–9 and space). The numerical digit data is one of the eleven values with the maximum confidence value. The number defining process uses this maximum confidence to identify the numerical data. This paper proposes 30 epoch times to train the data set because the accuracy of the validation set can converge to 100% at this epoch. This paper uses a local detection and recognition training set. The local detection training set has 40 sample images. The local recognition training set has 537 sample digits.

In this paper, the data set for the experiment was manually recorded from wire pulling machines, as shown in Fig. 13. The Y-axis is the distance of the wire in meters. The X-axis is the time in minutes. The data frequency is two sampling data images in one minute. The graph showed the pattern of the sampling data. When the distance of the wire reaches the specified range, the distance will reset to zero, and the process will be repeated.

Table 1. Parameters setup

Parameter	Value
# nodes in 1st convolution layers of feature extraction (ReLU activation function)	4-8-16
# nodes in 2nd convolution layers of feature extraction (ReLU activation function)	2-4-8
# nodes in a fully connected layer of classification (ReLU activation function)	16
# nodes in output layers (Softmax activation function)	11

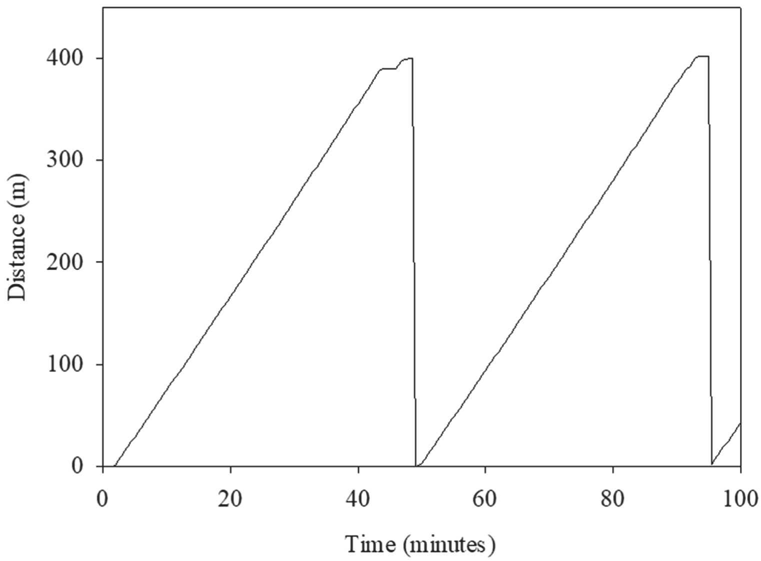


Fig. 13. The real data set

4.2 Accuracy of ISS Framework

This session shows the ISS framework performance. The algorithm is affected by changing the number of nodes. To increase the accuracy of the ISS algorithm, the simulation setup changes the number of nodes in the CNN model 8 trail set (No 1–8). The simulation uses two hidden layers for convolution layers of feature extraction and one hidden layer for classification.

Table 2. Accuracy of ISS framework

No.	Number of nodes			AC of ISS (%)	AC of P-P (%)
	Layer 1	Layer 2	Layer C		
1	4	2	16	71.74	86.88
2	4	8	16	89.32	91.70
3	8	2	16	88.61	91.35
4	8	4	16	90.40	90.07
5	8	8	16	90.44	91.04
6	16	4	16	89.05	91.22
7	16	6	16	90.78	90.53
8	16	8	16	91.11	91.12

Table 2 shows the number of testing simulations and accuracy. The number of nodes shown in each layer 1, 2, and C, respectively. The accuracy of the SSDR (AC of SSDR) procedure and the accuracy of the post-processing (AC of P-P) calculated from the inverse of the percentage error as follows in Eq. 5. The AC_t is accurate at time t. D_t is the real data at a time t. P_t is the decided data at a time t.

$$AC_t = 100 - \left(\frac{|D_t - P_t|}{D_t} * 100\right) \tag{5}$$

The average accuracy of ISS is 87.68%, while the average post-processing value is 90.48%. However, post-processing reduces spike and noise from the ISS framework, as shown in the table as set numbers 1, 2, 3, 5, 6, and 8. The standard deviation accuracy of ISS is 6.5%, but the P-P reduces the standard deviation accuracy up to 1.54%.

Figure 14 shows the graph to compare between the real data and the ISS output data (No 5). The Y-axis is a distance of the wire in meters. The X-axis is the time in minutes. As the 24th number of data, the SSDD procedure fails; it cannot find the numerical data. At the 69th number of data, the SSDR procedure fails because of the wrong decision.

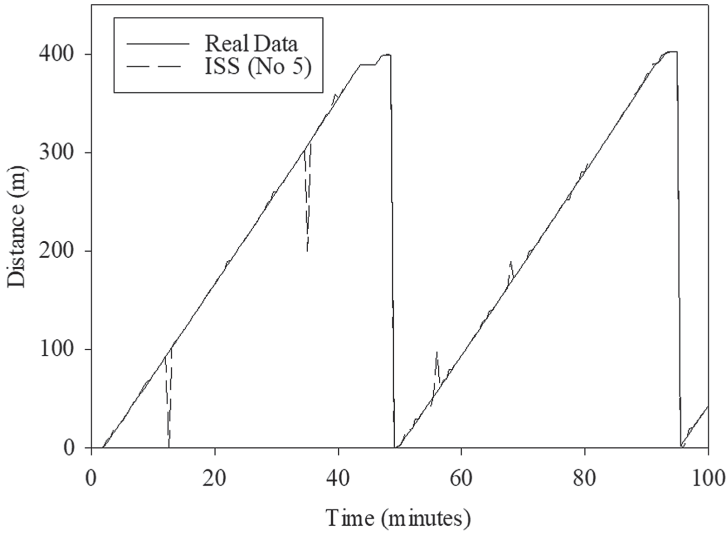


Fig. 14. The real data set comparison with data set from ISS output (model No 5).

5 Conclusion

This paper proposed the real-time seven-segment display detection and recognition online using CNN system, RSDC system. This system uses a camera module to capture a seven-segment display from the machine. The camera module sends the captured image via a wireless network to the server. The server uses the ISS algorithm to real-time process images into numbers. The ISS algorithm has the following operations: SSDD, SSDR, and Post-processing. The CNN algorithm is applied to the detection and recognition process (i.e., SSDD and SSDR procedure). The proposed ISS framework in the

RSDC is applied as the detection and recognition process can identify the numerical data accuracy up to 91.11% without post-processing. The average accuracy by adjusting the number of the CNN nodes in the detection and recognition process is 87.68%. However, when the accuracy of the SSDR procedure is less than 90%, the post-processing procedure can increase the accuracy close to 90% or more. The average accuracy after the post-processing procedure is applied increases from 87.68% to 90.48%. The result shows that RSDC can continuously capture photos and processes image in real-time. Images are precisely converted to numerical data using the ISS framework.

References

1. Li, Y., Qian, H.: Automatic recognition system for numeric characters on ammeter dial plate. In: 2008 The 9th International Conference for Young Computer Scientists, pp. 913–918. IEEE, November 2014
2. Ghosh, S., Shit, S.: A low-cost data acquisition system from digital display instruments employing image processing technique. In: 2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI), pp. 1065–1068. IEEE, September 2014
3. Shenoy, V.N., Aalami, O.O.: Utilizing smartphone-based machine learning in medical monitor data collection: seven segment digit recognition. In: AMIA Annual Symposium Proceedings, vol. 2017, p. 1564. American Medical Informatics Association (2017)
4. Qadri, M.T., Asif, M.: Automatic number plate recognition system for vehicle identification using optical character recognition. In: 2009 International Conference on Education Technology and Computer, pp. 335–338. IEEE, April 2009
5. Alegria, E.C., Serra, A.C.: Automatic calibration of analog and digital measuring instruments using computer vision. IEEE Trans. Instrum. Meas. **49**(1), 94–99 (2000)
6. Liang, C., Yang, W., Liao, Q.: An automatic interpretation method for LCD images of digital measuring instruments. In: 2011 4th International Congress on Image and Signal Processing, vol. 4, pp. 1826–1829. IEEE, October 2011
7. Popayorm, S., Titijaroonroj, T., Phoka, T., Massagram, W.: Seven segment display detection and recognition using predefined HSV color slicing technique. In: 2019 16th International Joint Conference on Computer Science and Software Engineering (JCSSE), pp. 224–229. IEEE, July 2019
8. Kulkarni, P.H., Kute, P.D.: Optical numeral recognition algorithm for seven-segment display. In: 2016 Conference on Advances in Signal Processing (CASP), pp. 397–401. IEEE, June 2016
9. Bonačić, I., Herman, T., Krznar, T., Mangić, E., Molnar, G., Čupić, M.: Optical character recognition of seven–segment display digits using neural networks. In: 32st International Convention on Information and Communication Technology, Electronics and Microelectronics, vol. 3, March 2015. http://morgoth.zemris.fer.hr/people/Marko.Cupic/files/2009-SP-MIPRO
10. Xing, L., Tian, Z., Huang, W., Scott, M.R.: Convolutional character networks. In: Proceedings of the IEEE International Conference on Computer Vision, pp. 9126–9136 (2019)
11. Ghugardare, R.P., Narote, S.P., Mukherji, P., Kulkarni, P.M.: Optical character recognition system for seven segment display images of measuring instruments. In: TENCON 2009 - 2009 IEEE Region 10 Conference, pp. 1–6. IEEE, January 2009
12. Tekin, E., Coughlan, J.M., Shen, H.: Real-time detection and reading of LED/LCD displays for visually impaired persons. In: 2011 IEEE Workshop on Applications of Computer Vision (WACV), pp. 491–496. IEEE, January 2011

13. Wannachai, A., Champrasert, P., Aramkul, S.: A self-adaptive telemetry station for flash flood early warning systems. In: 2017 14th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), pp. 645–648. IEEE, June 2017
14. O'Shea, K., Ryan, N.: An introduction to convolutional neural networks. J. arXiv preprint arXiv:1511.08458 (2015)