Automated Single-Pole Double-Throw Toggle Switch Pin Inspection using Image Processing and Convolutional Neural Network Techniques

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***Abstract*—The single-pole double-throw toggle switch bent pin inspection is an indispensable step in the switch production process. However, the traditional inspection process is conducted in manual work, and this may result in misunderstanding and reduces the manufacturing efficiency due to exhausted humans. To overcome these problems, the automated single pole-double throw toggle switch bent pin inspection method by using image processing and convolutional neural networks is proposed. Our proposed method can be achieved to inspect whether normal or abnormal bent pin of these toggle switches without sorting and no positioning arrangement. Our proposed method consists of five main steps: The first step, the HSV color segmentation is used for background extraction. Next step, the morphological opening, and closing operation are applied for handling noise and holes that conspicuously affect the system's ability to identify the extracted object accurately. Next step, the minimal enclosing rectangle and angle of rotation are calculated for identifying the positions of the disorder toggle switch. Next step, the CNN is used for locating pins in order to extract only the pins out from the binary switch image. In the final step, the average summation of the white pixel is calculated for classifying normal and abnormal bent pins. The experimental results obtained by our proposed method are statistically described as accurate compared to many different methods based on the single pole-double throw toggle switch bent pin inspection. Results show that our proposed method provides high accuracy than other comparative methods with a mean accuracy of 0.9940 from 6,270 images and uses mean time-consuming 0.3385 seconds.**

***Index Terms*—SPDT Toggle Switch, Pin Inspection, Image Processing, CNN**

I. Introduction

The toggle switch is an electrical component actuated by moving a lever mechanism back and forth to connect or disconnect the conducting path in an electrical circuit, diverting the electric current or interrupting it from one conductor to another. Toggle switches are available in many different configurations, styles, sizes, and various ratings for voltage. Generally, the toggle switch can be categorized by the term used into four types: Single Pole-Single Throw (SPST), Single Pole-Double Throw (SPDT), Double Pole-Single Throw (DPST), and Double Pole Double Throw (DPDT). The Pole refers to the number of circuits are controlled by the switch: The Single Pole (SP) switches control only one electrical circuit, and The Double Pole (DP) switches control two independent circuits. The Throw refers to the number of close a circuit position: Single Throw (ST) switches close a circuit at only one position. Double Throw (DT) switches close a circuit in the left position as well as the right position.

The SPDT toggle switch has a single input that controls only an electrical circuit, and it can connect to two outputs circuits in both left and right positions. This switch has a three-pin and only one lever mechanism. The SPDT toggle switch manufacturing process is diverse and complex consists of many processes. The appearance inspection process is one of the main important processes in order to find foreign particles, stains, flaws, and chipping to prevent an outflow of defective workpieces with an activity such as checking, measuring, examining, testing, and comparing the results with specified requirements. In this process, the checkpoints of the SPDT toggle switch are differentiated into three inspection parts: pin, body, and lever, as shown in Fig. 1 with the red rectangle from left to right, respectively.

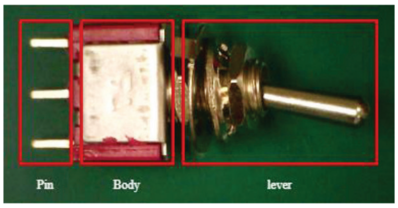


Fig. 1. SPDT Toggle switch inspection parts

The pins inspection for SPDT toggle switches will be measured the dimensions and checked the abnormal that happens to its toggle switch by human visual inspection and automated sensing. Moreover, the examination of a ton of product sample size, many operators are assigned to support the production for a long period of time, and this may result in misinterpretation and reduce the manufacturing efficiency due to exhausted human [1], [2].

Nowadays, machine vision technology has been widely used in electrical components, mainly including the inspection crack, bent, corrosion, texture, degree, straightness, deflection, and other defects [3]. This technology has a more obvious advantage than human manual checking and provides high efficiency and reliability [4]. However, there are little researches on electronic component base on pin inspection by using machine vision. Yewei Xiao's research of Xiangtan University proposed pin detection in the transmission line using pyramid multi-level to scaling image. The cascade detection and no-maximum suppression are used to identify the candidate boundary of the pin in the transmission line, and a convolutional neural network is applied to classify the status of the fastener, whether missed or unmissed pin. His proposed method provides higher accuracy and runs faster than other comparative machine learning methods. However, this method does not cover all of the fastener pin styles [5]. Wu Weihao research of the China Jiliang University proposed defective electrical connector inspection based on machine learning method by using Yolo v3 efficiently algorithm with Darknet-53 as a Convolutional Neural Network (CNN) that acts as a backbone. The mainly defective characteristics include solder point surface, ground wire wrong welding, and inner and outer ring. The defective locations are around the surface and pin of the connector. The qualitative and quantitative experimental results show that his improved Yolo v3 has better performance and runs faster for detection than other competitive machine learning methods. However, the accuracy and speed of his method do not meet the needs of modern automated production lines [6]. Lu Jiayu's research of the Harbin Institute of Technology proposed electrical connector types classification based on the pin position by using a gray-scale centroid algorithm for pin positioning and a template matching algorithm based on gray features for pin recognition in order to classify the type of connector. His main research area is only classified the type of connector; however, the primary defective pin detection has not been performed [7]. Pallabi Ghosh's research of the Institute of Technology Kharagpur proposed automated defective pin identification based on recycled counterfeit integrated circuits using supervised and unsupervised machine learning methods. A convolutional neural network is applied to classify the pin status, whether normal, bent, and corroded pins, from RGB and depth map images. Furthermore, two unsupervised learning methods are used to identify bent pins with 3d construction from depth map images. K-means is used to detect corroded pins with Laws Texture energy measures method for extracting the feature vectors. His proposed approach has been highly accurate in identifying both corroded and bent in counterfeit integrated circuits. However, the speed of this proposed method has not been improved [8]. Du Fuzhou research of Beijing University of Aeronautics and Astronautics proposed the multi-type electrical connector classification based on a binocular vision by using a contour fitting algorithm to locate the pins in the connector and uses Support Vector Machine (SVM) to classify various types of pins. His proposed method has been computed with high accuracy and more efficiency than other methods. However, the speed of his proposed method has not been calculated and it has not been applied to the real production line [9]. Someyot Kaitwanidvilai of King Mongkut Institute of Technology Ladkrabang proposed the integrated circuit pins inspection using the wavelet transform and discrete Fourier's transform to extract the interesting features for classifying the integrated circuit pins pattern. His proposed technique gains a higher average maximum cross-correlation than other methods. However, the defective type has not been classified and has not been applied to the real production inspection process [10].

In summary, there are few researches on inspection of the defective pin of electrical components. The traditional image processing and machine learning techniques are often used for electronic components inspection, which solves problems such as crack, bent, corrosion, and other defective characteristics. However, most of the researches based on the defective pin of electronic component identification are facing problems in poor real-time performance, limit position identification, unable to work on unsorting images, and does not match the modern automated production lines. Our research proposes a new combination of methods by using image processing and CNN techniques to identify abnormal bent pins of SPDT Toggle switches in a different position and disordering and. Our proposed method will be applied into the real production process.

The remainder of this paper is organized as follows: The first part is aimed at introducing the defective types of SPDT toggle switches and their existing problems. The second part describes the experimental setup for pin inspection with image processing and CNN techniques. Next, the results of the experiment were carried out by comparison with other competitive methods. The fourth part summarizes the paper.

II. Methodology

In the quality inspection process at the defective inspection station, the SPDT toggle switches are conveyed through a belt at a constant speed, and there are placed in different positions, non-stick together, disorder, and unsorting. When the toggle switches pass through a proximity sensor, then a sensor will be activated and sent a signal to a control unit to capture an image of these toggle switches with an installed camera. Fig. 2 shows example RGB images of SPDT toggle switches. These images consist of two types of checked pins are the abnormal bent pin and the normal pin. In the experimental setting, the abnormal bent pins are simulated by different patterns due to extreme testing and validation of the proposed method.

Our proposed method is applied both image processing and deep learning techniques. Fig. 3. gives an overview of our method consists of five main steps: The background image extraction based on HSV Color segmentation, Noises and holes removal using morphological opening and closing, the toggle switches region identification using minimal enclosing rectangle and angle of rotation calculation, pin identification by applying the deep learning-based convolutional neural network architecture and pin inspection by considering the average of summation of the white pixel.

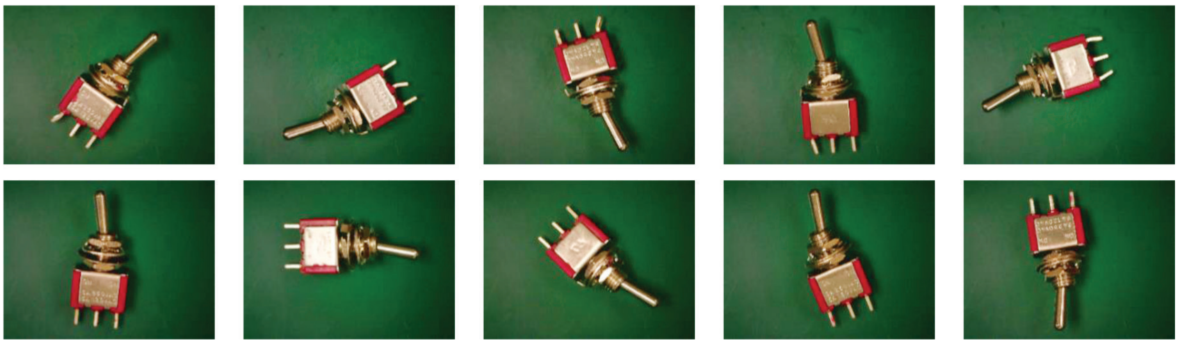


Fig. 2. SPDT toggle switch images with the top row represents abnormal bent pint toggle switches and bottom row represents normal toggle switches.

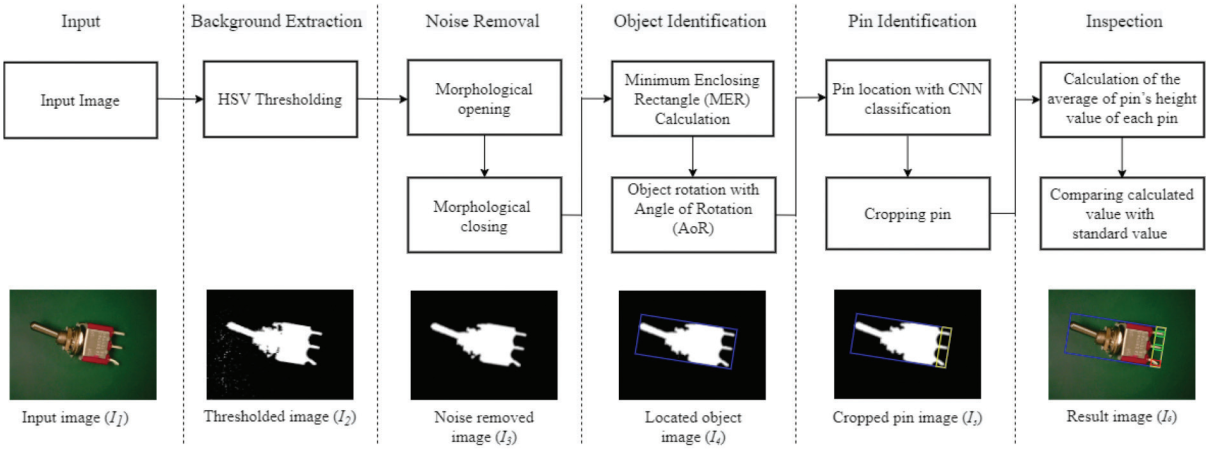


Fig. 3. Proposed method

A. Background Extraction

The first step of object identification using image processing techniques is background extraction [11]. Considering the SPDT toggle switch images color, the belt screen or background is green and it differentiates from the switch color ostensibly. The HSV color segmentation method can be achieved to extract it apart from each other by converting I_0 from the RGB color space where R, G, B represent red, green, and blue components respectively with a value between 0-255 into the HSV color space using the following equations1-3 [12]. The HSV color space is very useful in image processing tasks that need to segment objects based on color according to the H (Hue) channel models the color, the S (Saturation) dimension models the dominance of that color, and the V(Value) dimension models the brightness. Then the background will be separated from the object by thresholding H and V values using equations 4 thus, the result is displayed in the binary image (I1).

$$H=\cos^{-1}\left\{\frac{\frac{1}{2}(2R-G-B)}{\sqrt{(R-G)^2-(R-B)(G-B)}}\right\} \tag{1}$$

$$S=\frac{\max(R,G,B)-\min(R,G,B)}{\max(R,G,B)} \tag{2}$$

$$V=\max(R,G,B) \tag{3}$$

$$I_1(x,y)=\begin{cases}1, & \text{if } 42<\text{H(x,y)}<160 \text{ and } \text{V(x,y)}<102\\ 0, & otherwise\end{cases} \tag{4}$$

Where $H(x,y)$ represents a Hue value of the coordinate (x,y). $V(x,y)$ represents a Value value of the coordinate (x,y).

B. Noise Removal

The most common problems after segmentation objects are noise and holes. The type of noise is a small white area spreads all over the image, and the hole is a background region surrounded by border-connected foreground pixels. The noise and holes can conspicuously affect the system's ability to rotate and identify the extracted object precisely, to overcome these problems, a series of post-processing methods are applied by using the morphological opening following a closing operation. The morphological opening operation erodes an image and then dilates the eroded image as the equation 5, and the morphological closing operation dilates an image and then erodes as the equation 6, both operations using the same size, shape, and structure element as the equation 7. The morphological opening operation is great for removing small noises. The closing morphological operation is useful for filling small holes while preserving the shape and size of the larger interested region in the image. The result is presented in the binary image (I_2).

$$I'=I_1\circ B=(I_1\ominus B)\oplus B \tag{5}$$

$$I_2=I'\bullet B=(I'\oplus B)\ominus B \tag{6}$$

Where $\oplus$ and $\ominus$ denote the dilation and erosion, respectively.

$$B=\begin{pmatrix}\vdots & \vdots & & \vdots\\ 1 & 1 & \cdots & 1\\ \vdots & \vdots & & \vdots\end{pmatrix} \tag{7}$$

Let B is a structure element with size 10x10

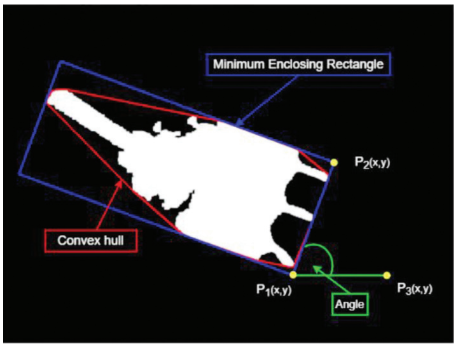


Fig. 4. The blue bounding rectangle is the MER applied result, the red area is the convex hull region and green angle is the angle calculated by AoR.

C. Object Identification

Since noise and hold were eliminated and only interested region is presented then the Minimum Enclosing Rectangle (MER) will be calculated. The MER is the method to compute the smallest bounding rectangle that contains the whole interested region by not required to be axis-aligned and constructed by a convex hull of the region [13]. The implementation of MER involves iterating over the edges of a convex polygon. For each edge, compute the smallest bounding rectangle with an edge coincident of all rectangles, shorting, and choose the one with the minimum area. The maximum distance between the projected vertices is the width of the rectangle, and the maximum distance between the projected vertices is the height of the rectangle [14]. The result of MER is shown in Fig. 4 as the blue bounding rectangle.

Determining the position of the pin in the MER is difficult and requires high accuracy. CNN is presented to determine the location of the pin in MER by learning from the dataset. However, the dataset is obtained from a cropped images with MER is not available, it is necessary to rotate these images into axis-aligned by finding the Angle of Rotation (AoR). Fig. 4 shows the AoR as the green angle, it is the angle formed by using two vectors u and v performed by the three points P_1, P_2, and P_3. P_1 is the lowest point in the vertical axis of the MER, P_2 is the ending point ordered clockwise staring from P_1, and P_3 is the point to the right of P_1 on the horizontal axis. The u and v can be calculated with equation 8. Therefrom, the AoR is calculated by using the invert of the law of cosines with equation 9. Finally, the toggle switch object will be cropped with MER and rotated with AoR, and the results are possibly arranged into four patterns by pin location: Bottom, Top, Right, and Left. The example results are shown in Table I.

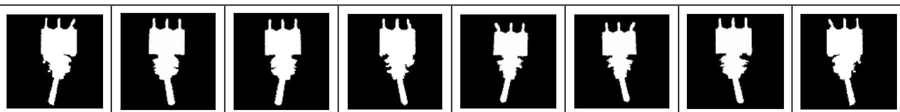
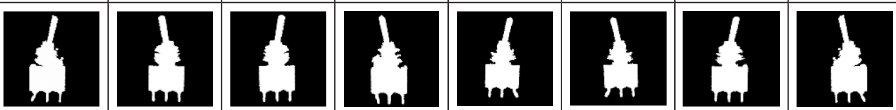
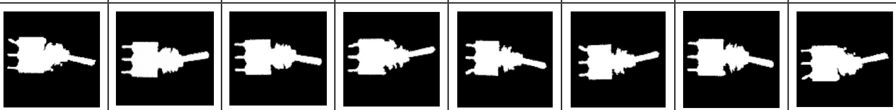
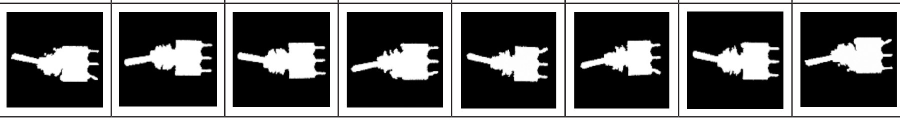
$$
\begin{aligned}
u &= (p1_x - p2_x, p1_y - p2_y) \\
v &= (p1_x - p3_x, p1_y - p3_y)
\end{aligned}
\tag{8}
$$

$$
\theta = \arccos\left(\frac{a \cdot b}{|a||b|}\right) \tag{9}
$$

D. Pin Identification

The pin location of the SPDT toggle switch in the image is unpredictable because the toggle switches are pressed in different positions. Once the MER and AoR were applied, the pin location has four possible alignment positions: top, bottom, left, and right inside bounding-box, as shown in Table I. Since this study is part of a larger project that intends to investigate all types of SPDT toggle switch abnormalities, such as bent pins, broken pins, broken levers, and damaged bodies. The inspection of SPDT switches necessitates the alignment of objects into similar patterns. The solution adopted should be adaptable and capable of dealing with all kinds of SPDT toggle switch abnormalities. Thus, the Convolutional neural network is proposed to classify the location of the pin in order to align the objects into similar patterns and it can be applied to use in difference of kinds of SPDT toggle switch abnormalities. The CNN is a class of deep neural networks commonly used to image classification jobs. The use of CNN requires a sufficient dataset and more complex processing to build a model for classifying multi-class of problems [15].

TABLE I
SAMPLE DATASET OF BINARY IMAGE OF SPDT TOGGLE SWITCH

Label	Class	Example	Sample
0	Bottom		250
1	Top		250
2	Right		250
3	Left		250

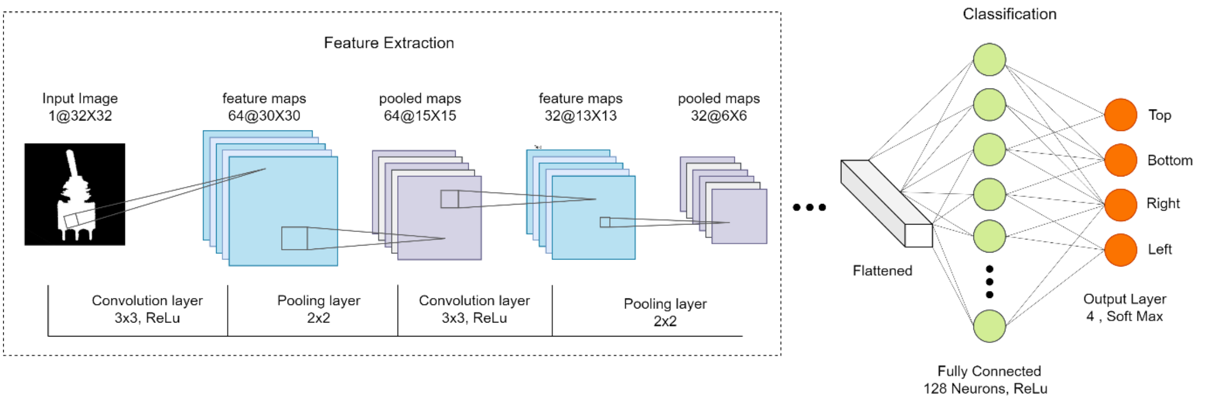


Fig. 5. Architecture of proposed CNN for pin location classification

The dataset consists of 1000 of the SPDT Toggle images and it is a collection of 4 distinct classes: Top, Bottom, Left, and Right. Each class is equally provided 250 images. All images are resized into 32x32 pixels and normalized all pixel values into the range 0-1. The used dataset is split into two parts for training and validating. The first spitted dataset is used to fit the model consists of 80% of all datasets, and the remaining 20% is used for validating.

Once the dataset was ready, the CNN model for pin location classification will be created. Typically CNN is a sequence of multi-layer that transforms one volume of activations to another through a differentiable function and commonly uses three main types of layers. They are a convolutional layer, pooling layer, and fully connected layer. The proposed model uses these layers stacked into five layers of network architecture, as shown in Fig. 5.

Layer-1 is the convolutional layer response to extracts the high-level features from the input image as a convolutional activity [15], [16]. Since the input image has been normalized, the image will be 32x32 (nxn) of the size. This layer is constructed by using 64 of the dimensionality of the output space (d), 3x3 of kernel size (f), 1 of strides (s), and 0 of padding (p). Since ReLu (Rectified Linear Unit) as an activation function was done. The feature maps will be presented with size 64@30x30 where 64 is the number of feature maps which is equal to the number of dimensionality of the output space, and 30 calculate from equation 10.

$$((n+2p-d)/s)+1 \tag{10}$$

Layer-2 is the max-pooling layer. This layer receives the input of size 64@30x30 from the previous layer to calculate the maximum value for each patch of the feature map [15], [16]. Thus, this layer consists of 2x2 of pooling size, 2 of strides (s), and 0 paddings (p). the After max-pooling operation, the feature maps will be presented with size 64@15x15 where 64 is the number of feature maps which is equal to the number of dimensionality of the output space, and 15 is calculate from equation 10.

Layer-3 is second the convolutional layer acts as Layer 1 to reduce feature maps dimensionality output [15], [16]. This layer works with the ReLu activation function and receives the input size 64@15x15 from the previous layer. This layer is created by using 32 of the dimensionality of the output space (d), 3x3 of kernel size (f), 1 of strides(s), and 0 of paddings (p). After this convolution operation, the feature maps will be presented with size 32@13x13 where 32 is the number of feature maps, and 13 is calculate from equation 10.

Layer-4 is the average pooling layer. This layer receives the input of size 32@13x13 from the previous layer to calculate the average value for each patch of the feature map [15], [16]. This layer consists of 2x2 of pooling size, 2 of strides (s), and 0 paddings (p). After the average operation, the feature maps will be presented with size 32@6x6 where 32 is the number of feature maps which is equal to the number of dimensionalities of the output space, and 6 is calculate from equation 10.

Layer-5 is a fully connected layer. Since the flattening has operated using the input from Layer-4, the flattened feature map will be 32x6x6=1152 dimensional vectors. These output vectors will be connected to every input perceptron by learnable weight. This layer computes the class score by using the soft-max activation function [15], [16]. The result presents an array size of four, where each of the four numbers corresponding to a class score representing the Left, Right, Top, and Bottom sides of SPDT toggle switches pin location.

The proposed model is trained by using the best parameter that is conducted in the experimental process, including the Adam as optimization algorithm, 100 epoch for training, 64 of batch size, and learning rate with 0.001. The proposed CNN model highly achieves 100% for training accuracy, whereas validation accuracy is 100%. Fig. 6 shows the confusion matrix of the impact of false class rate, it clearly shows that the proposed CNN model provides zero false in every class rate. Therefore, it is observed that the proposed model trains effectively, keeping no losses and owing to testing accuracies. Thus, the proposed model is least affected by the over-fitting problem and can be efficiently utilized to classify the pin location to crop pin with 100% accuracy.

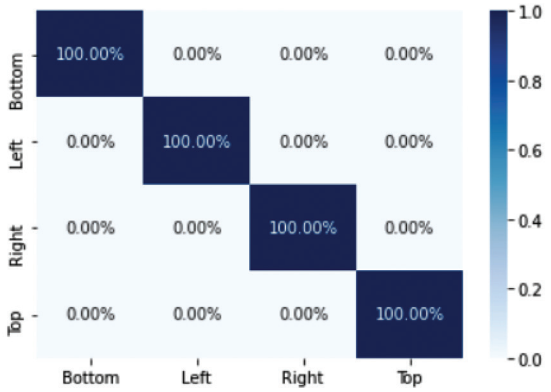


Fig. 6. A confusion matrix analyses of the proposed CNN model

Since the pin of SPDT toggle switch in binary image location was identified by predicting with the proposed CNN model then these pin will be cropped according to the prediction result as shown in Fig. 7 (a). The cropped pin will be rotated according to its class as following: Bottom, Left, Top and Right are rotated with 0°, 90°, 180° and 270° respectively. The rotated pin images are always arranged at the bottom as shown in Fig. 7 (b).

E. Inspection

The abnormal bent pin is very similar to the normal pin of SPDT toggle switch in case of slight bent pin and these pins are very difficult to differentiate whether normal or bent pin. However, differentiating these pins requires a thresholding with specific parameters obtained from the various properties of its pins. The width and height of the pin are the significant considered parameters since the bent directly affects to the width and height of the pin.

Once the pins were located and each pin was cropped from the binary image of the SPDT toggle switch as shown in Fig. 7 (b) The width of pins is considered by counting the number of columns of a cropped pin. So, the width of the bent pin is greater than the normal pin as shown in Fig. 7 (c) that this parameter may be used as a thresholding parameter. However, Fig. 8 (a) shows the distribution of the width of normal and abnormal bent pins are overlapping between the maximum values distribution of normal pins and the minimum values distribution of abnormal bent pins, thus the width of the pin is out of use.

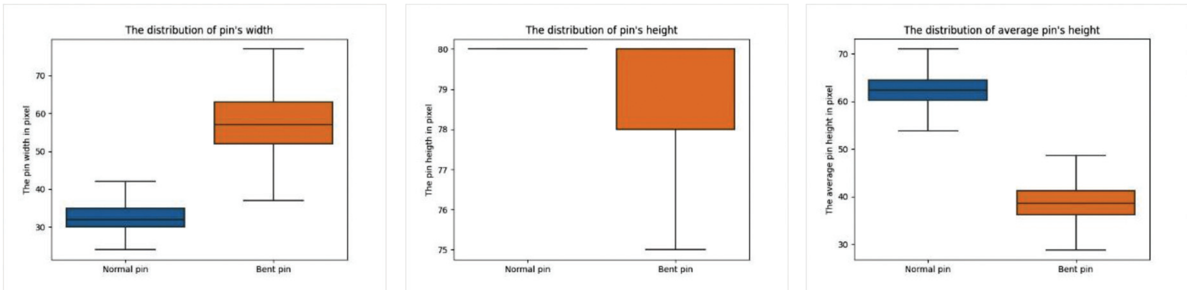
The height is an important parameter for considering to differentiate normal and abnormal bent pins. This height parameter can be calculated in two ways: maximum height and average height. The maximum height is calculated by finding the highest columns of a cropped pin. So the maximum height of the normal pin looks different from the bent pin, as shown in Fig. 7 (c) that this parameter should be used for thresholding. However, the distribution of the maximum height of normal and abnormal bent pins shows that there is overlapping between the minimum value distribution of normal pins and the maximum value distribution of abnormal bent pins, as shown in Fig. 8 (b). Hence, the maximum height of the pin is not good for thresholding.

The average height is calculated by averaging the summation of the white pixel in each column (vertical axis) of a cropped pin. So the average height of the normal pin should be greater than the abnormal bent pin as the maximum height parameter. So the distribution of the average height of normal and abnormal bent pins is significantly different from each other, as shown in Fig. 8 (c) that this parameter can differentiate between the normal pin and abnormal bent pin.

The average height is used to differentiate between the normal and abnormal bent pins of the SPDT toggle switch. Each pin is calculated for this average height value and it is compared with the standard value obtained from non-overlapping range of the distribution of average height. Fig. 8 (c) shows a range of non overlapping range between the maximum distribution of average height of abnormal bent pin and the minimum distribution of average height of normal pin. If the calculated value is lower than the standard value, the pin is bent; on the other hand, if the calculated value is higher than the standard value, the pin is normal.

(a) (b) (c)

Fig. 7. (a) The cropped pin in binary image of SPDT toggle switch, (b) the extracted each pin, (c) Graph of summation of with pixel in column of each pin



(a) (b) (c)

Fig. 8. The distribution of parameter of SPDT toggle switch. (a) The distribution of pin's width parameter, (b) The distribution of pin's height parameter, (c) The distribution of average pin's height parameter

III. Result and Discussion

In this section, the results of our proposed method for SPDT toggle switch pin inspection are presented. In order to test the effectiveness of our proposed method, many approaches including of supervised learning, transfer learning, feature matching, template matching, and other images processing designed for SPDT toggle switch pin inspection were conducted to compare the inspection results that were obtained from several testing images. All methods in this experiment were programmed in Python and all experiments were implemented on an NVIDIA DGX1 AI cloud server, CPU Dual 20-core Intel Xeon E5-2698 v4 2.2 GHz, GPUs 8X NVIDIA Tesla V100, and 512 GB 2,133 MHz DDR4 of system memory. The total of testing image contains 4,008 images by using 2,261 images for normal pin and 1,747 for abnormal bent pin of SPDT toggle switches. All testing images are the color image with the same size of 1,280x960 pixels and each image taken with a same focal length in a same environment.

Fig. 9 shows the example result images obtained from our proposed method. The region of the SPDT toggle switch in image was drawn with the blue rectangle and its pin location was drown with the yellow rectangle. The red rectangle indicates the abnormal bent pin, on the other hand the green rectangle indicates the normal pin. In order to evaluate the quality level of the results obtained form our proposed method and the other methods, the various matrix-based performances metrics are used as performance measurements, these metrics consist of five main indicators: accuracy, precision, recall, F-measure and time-consuming [17], [18]. Table II shows the results of our proposed method in six runs, the mean accuracy of our proposed is 0.9940 and the mean of time-consuming is 0.0230 second, the standard deviation of all indicators are very small since our proposed method provides the result clustered around the mean. Table III shows the comparative results in every methods and Table IV shows the comparative results by group of methods.

Since supervised learning can differentiate data through learning process with labeled dataset. Therefore, KNN, SVM and CNN are used to classify normal and abnormal bent pin from gray scale images of SPDT toggle switch [19]. The mean accuracy of these methods is 0.9392 and mean time-consuming is 0.2483 where CNN obtains the highest accuracy with 0.9475 and uses least time-consuming with 0.2206 second while KNN obtains the lowest accuracy with 0.9275 and uses the most time consuming with 0.2725 second. Comparison results between all supervised leaning methods and our proposed method, it was found that our proposed method was more accurate but took more processing time than supervised learning methods. However, all supervised learning approaches can tell the difference between a switch with a normal pin and one with a bent pin, but it can't tell the difference between a switch with a little bent pin and it fail to locate the bent pin in a switch but the proposed method succeeds.

Transfer learning is the subset of supervised learning uses to classify color images as the same as supervised learning. However, this method uses smaller dataset than supervised learning methods [20]. In this research, seven candidate methods of transfer learning are used: Dense-Net, Inception, Mobile-Net, Res-Net, VGG16, VGG19 and Xception. These methods provide mean accuracy with 0.9014 and mean time-consuming with 0.2886 second where Dense-Net obtains the highest accuracy with 0.9725 but it takes the most consuming-time with 0.4636 seconds while Mobile-Net obtains lowest accuracy with 0.7825 but it takes the least consuming-time with 0.1870. Moreover, this Dense-Net transfer learning provides higher accuracy than all supervised learning methods. However, all transfer learning methods provide poorer accuracy than our suggested method for the same reasons as supervised learning approaches.

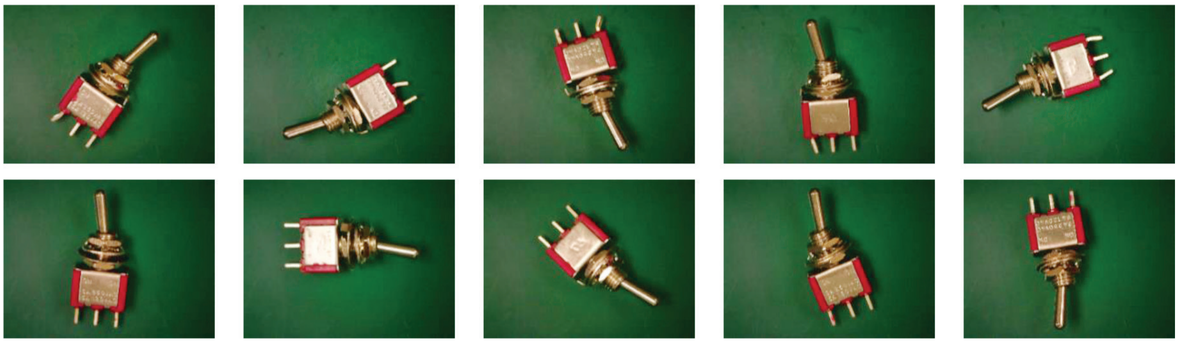


Fig. 9. The example results obtained from our proposed method

TABLE II
THE RESULTS OF OUR PROPOSED METHOD IN SIX RUNS

No	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)	Time (sec)
1	0.9941	0.9967	0.9914	0.9941	0.3222
2	0.9940	0.9971	0.9909	0.9940	0.3630
3	0.9940	0.9971	0.9909	0.9940	0.3530
4	0.9940	0.9971	0.9909	0.9940	0.2971
5	0.9940	0.9971	0.9909	0.9940	0.3584
6	0.9940	0.9971	0.9909	0.9940	0.3374
Mean	0.9940	0.9970	0.9909	0.9940	0.3385
Std.	0.00003	0.0001	0.0001	0.00003	0.0230

TABLE III
COMPARISON RESULTS OF OUT PROPOSED METHOD AND OTHER METHODS BASED SPDT TOGGLE SWITCH BENT PIN INSPECTION

Methods		Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)	Time (sec)
Supervised Learning	KNN	0.9275	0.9314	0.9275	0.9273	0.2725
	SVM	0.9427	0.9038	0.9533	0.9247	0.2518
	CNN	0.9475	0.9555	0.9475	0.9490	0.2206
Transfer Learning	Dense Net	0.9725	0.8901	0.8625	0.8644	0.4636
	Inception	0.8125	0.8128	0.8125	0.8125	0.2783
	Mobile Net	0.7825	0.7825	0.7825	0.7825	0.1870
	Res Net	0.9725	0.9735	0.9725	0.9725	0.2397
	VGG16	0.9250	0.9300	0.9250	0.9252	0.2324
	VGG19	0.9525	0.9540	0.9525	0.9525	0.3021
	Xception	0.8925	0.9016	0.8925	0.8930	0.3176

TABLE III
Comparison Results of Out Proposed Method and Other Methods Based SPDT Toggle Switch Bent Pin Inspection (Con.)

Methods		Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)	Time (sec)
Feature matching	SURF	0.4809	0.2068	0.4577	0.2849	0.6378
	MSER	0.5128	0.2169	0.5315	0.3080	0.6418
	BRISK	0.5208	0.2229	0.5514	0.3174	0.6396
Template matching	Square Difference	0.5300	0.2200	0.5789	0.3188	16.257
	Correlation Coefficient	0.5446	0.2772	0.5957	0.2654	7.8490
	Cross Correlation	0.5300	0.2200	0.5789	0.3188	7.6981
Other	PCA	0.5156	0.2286	0.5365	0.3206	0.2279
	MER+AOR	0.5254	0.2655	0.5530	0.3588	0.2205
Proposed Method		**0.9940**	**0.9970**	**0.9909**	**0.9940**	**0.3385**

TABLE IV
Mean of Each Performance Measurement of Different Methods

Method	Accuracy (%)		Precision (%)		Recall (%)		F-measure (%)		Time (sec)	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Supervised Learning	0.9392	0.0085	0.9302	0.0211	0.9427	0.0110	0.9336	0.0108	0.2483	0.0213
Transfer Learning	0.9014	0.0711	0.8920	0.0657	0.8857	0.0656	0.8860	0.0655	0.2886	0.0824
Template matching	0.5348	0.0068	0.2390	0.0269	0.5845	0.0079	0.3010	0.0251	10.601	3.9996
Feature matching	0.5048	0.0172	0.2155	0.0066	0.5135	0.0403	0.3034	0.0136	0.6397	0.0016
Other	0.5205	0.0049	0.2470	0.0184	0.5447	0.0082	0.3397	0.0191	0.2242	0.0037
Proposed Method	**0.9940**	**0.00003**	**0.9970**	**0.0001**	**0.9909**	**0.0001**	**0.9940**	**0.00003**	**0.3385**	**0.0230**

Template matching and feature matching are a technique in digital image processing for finding small parts of an image which match a template image and feature of the object respectively [21], [22]. Our experiment uses these methods to address the SPDT toggle switch and its pin in an image and uses our inspection method for determining normal and abnormal bent pins of the toggle switch. However, the mean accuracy of both methods is lower than our mean accuracy of the proposed method and it's mean time-consuming is higher than the mean time-consuming of our proposed method. Moreover, F-measure and precision of template matching and feature matching method are very low because the weighted harmonic mean is the imbalanced distribution of classes with accuracy. Once the object has less rotation, template matching and feature matching perform effectively. However, if the object has a lot of rotation, it won't be able to locate it. Since the switches in this study are arranged without ordering and wide range of rotation, Template matching and feature matching are unable to locate the position of this switch as effectively as they should resulting in lower accuracy than the proposed method.

Principle component analysis is a statistical procedure that extracts two important parameters are eigenvectors and eigenvalues from a binary objects in the image [23]. These two parameters are used to calculate the angle between an object and the horizontal axis. This research uses the calculated angle to rotate the SPDT toggle switch object in the image and its pin is always on the bottom of the object. Our inspection method will be applied for pin inspection. However, the results of this method are not different from the previous method for the same reason, the overall efficiency is lower than the proposed method.

In summary, even though all of the methods presented have a similar task to inspect the pin of SPDT toggle switches, our proposed method able to produce better accuracy results than other competitive methods. Moreover, our proposed method can distinguish between the normal pin and abnormal bent pin, and it can locate only specific abnormal bent pin of SPDT toggle switch while the other cannot be performed. However, our proposed method takes more the time-consuming than the supervised learning and transfer learning method because the abnormal bent pin identification process is quite time-consuming but it is worth it because it can clearly identify abnormal bent pin address which leads to further improvements in production quality.

IV. Conclusion

In this paper, combining image processing and machine learning techniques to inspect the bent pin of the SPDT toggle switch is proposed. The major contribution of this work is the successful development of an effective methodology, in which the image processing is implemented to extract the background out from the image using HSV color segmentation, remove noise and hole based morphological operation, locate toggle switch using MER and AoR, pin identification-based CNN classification and pin inspection by considering the average of summation of white pixels in the vertical. Furthermore, a detailed comparison between the proposed method and other methods including supervised learning, transfer learning, template and feature matching, and other image processing methods are presented in our experiments.

The results obtained from our proposed method provide high accuracy for pin inspection than other competitive methods and our proposed can differentiate between normal and abnormal bent pins. In addition, the proposed method is reliable and highly effective from the perspective of solution quality. The proposed method will be applied in the actual industry to improve the accuracy of the pin inspection for toggle switch products.

However, there is still conducted in a controlled environment for improvement in the capability of the proposed method. Applying in real industry processes should guarantee the parameters suit the industry environment to avoid noise and error in order to provide the highest accuracy. The future work is developing the inspection method for handling every defective type of the toggle switch and improving the speed of the method.

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