Application of AI deep-learning technique to the detection of internal misaligned and defective screw nuts

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Abstract

As a result of regulations and requests, most fasteners for the automotive industry require a 100% full quality control inspection. Conventional optical inspection machines are unable to efficiently provide 100% full quality control inspection as it is time consuming and difficult to easily detect defects and flaws. This paper focuses on the development and application of a convolution neural network (CNN) of an AI deep-learning technique for the internal thread measurement of misaligned fasteners. Integration of an optical hardware system and a software system platform is included. It is thus similar to upgrading the hardware and software system platform of conventional optical inspection machines. Utilizing the machine vision hardware, the system is capable of capturing an image of an internal thread of the fastener. In the software platform system, a CNN of deep learning is applied to detect and determine defects or flaws in the internal thread of the fastener.

Keywords: Fastener, Internal thread, Convolution neural network (CNN), AI deep learning

1. Introduction

This research came about as part of the competence promotion project of Kaohsiung Renwu and Yanan Industrial Parks supported by the Ministry of Economic Affairs of Taiwan, Republic of China. After interviewing more than 50 fastener manufacturers, we found that a need shared by many is an upgrade of their inspection facility to satisfy the demand for 100% full quality control in the future. Improvement in identifying the internal thread of misaligned fasteners in inspection is just one of the unique needs of manufacturers. Against this background, the development of an efficient and effective inspection technique is extremely important and is thus the main purpose of this paper.

A typical internal screw nut is shown in Fig. 1.1. It is extremely difficult to observe the entire thread because the diameter of the screw nut is very small. The conventional method of inspecting these internal screw nuts involves using a thread plug gauge to examine the tightness between the internal screw nuts and the thread plug gauge. If the internal screw nut has a defect in the line of thread, the thread plug gauge will be difficult to pass through. All such screw nuts should be eliminated.

There is another type of defect observed in internal screw nuts that may pass this test method and inspection without any glitches, namely, the misaligned internal screw nut. In

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these screw nuts, the line of internal thread is intact and the appearance is perfect. In order to compensate for this limitation, a standard thread plug gauge with a flange is utilized to examine internal screw nuts to identify defects and misalignment, as shown in Fig. 1.2. It is of note, however, that inspectors must turn the thread plug gauge to the bottom to check if there is any gap between the flange of the thread plug gauge and the internal screw nut. It is easy to imagine that, after conducting thousands of tests, some misaligned internal screw nuts may slip by unnoticed due to human error.

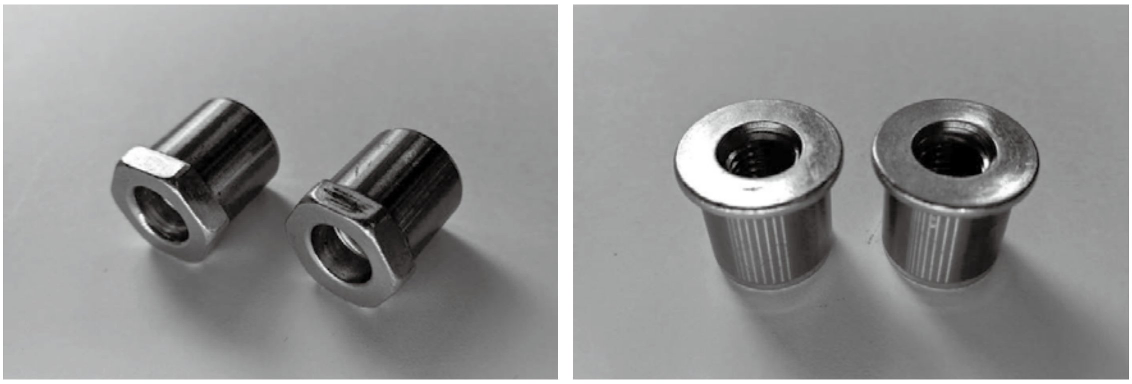


Fig. 1.1 Typical internal screw nuts are requested for 100% quality inspection.

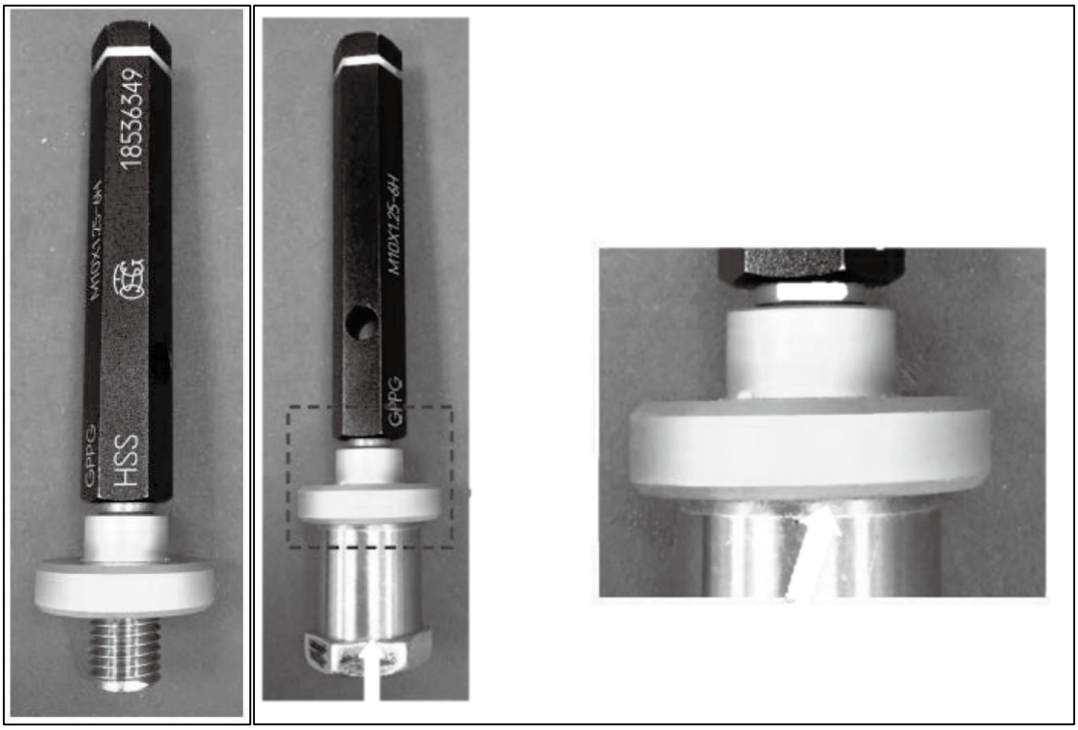


Fig. 1.2 Thread plug gauge with a flange for internal screw nut inspection.

The type of internal screw nut used in this study is the M10 screw (20 mm height and 20 mm diameter, including flange). The isometric view and the side view of this screw nut is shown in Fig. 1.3.

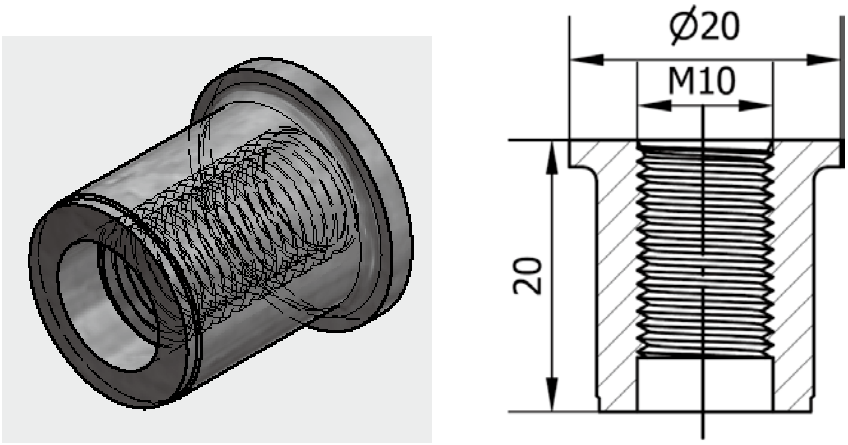


Fig. 1.3 The isometric view and side view of an internal screw nut.

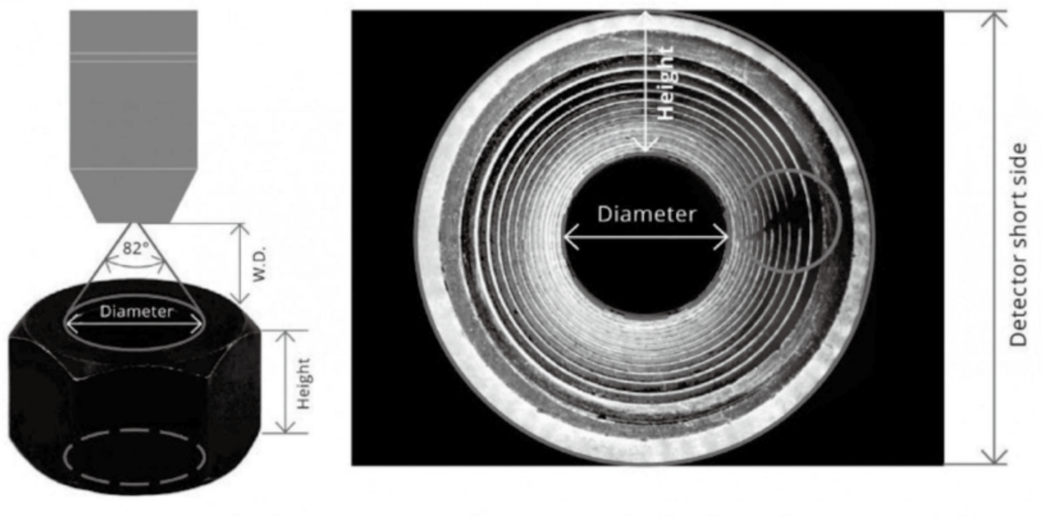
2.Pericentric hole inspection lens for internal screw nuts

In order to increase the production rate of fasteners, a great deal of research has been conducted on thread inspection and measurement using online 3D computer vision systems. Due to the visual difficulty involved in the thread inspection of internal screw nuts, a limited amount of research can be found on this issue [1,2]. For example, Song et al. [3] used a deep convolution neural network (CNN) method to detect micro-defects on metal screw surfaces. Liu [4] studied the 3D polarized scattering measurement of thread structure. Most researchers, however, focus on the inspection and measurement of the external thread. These efforts provide a solid foundation of technology for application to internal thread inspection.

For internal thread inspection, Perng et al. [5] designed and developed an auto-inspection system for defect detection. Shih [6], Lee [7], and Hong et al. [8] contributed to the optical or non-contact inspection of internal screw threads. In order to obtain precise measurement of the thread starting point and the dimensional features, one researcher used a non-contact high-precision laser sensor that employs a motorized periscope to acquire images of the internal surfaces [8]. Another used innovative machine vision: a line-scan technique that uses a charge-coupled device (CCD) camera with a "sight pipe" panoramic optical device to retrieve the image. Next, a sequence of partial wall images of an internal thread is reconstructed into a two-dimensional (2D) unwrapped image. Without the aid of AI methods, these research groups use conventional image-processing methods to deal with defects. One common concern with these methods is that they are very time consuming and they have an unproductive effect on the automation process.

In the previously mentioned inspection system, line scan cameras are usually employed to inspect the inner and outer surfaces of the internal thread part. To retrieve a full image of the circular thread line, each part has to be rotated in front of the line scan cameras, which is costly and time consuming.

Owing to the incredible progress of optical instruments, a hole inspection optics for a 360-degree inside view has been developed for devices with cavities and pits [9]. It can retrieve both the bottom of a hole and its vertical walls in an image without part rotation. The operation algorithm of this optical lens is shown in Fig. 2.1 and is easy to be interpreted. What we have to determine is that the "r" ratio indicates the detector area and the hole inner walls. This selected value is closely related to the inner diameter and height of the internal thread nuts.



$$r(\%) = \frac{\text{Side view height (px)}}{\text{Detector short side (px)}} * 100$$

Fig. 2.1 The detector area gets covered by the image of the hole's inner walls. [9]

3. Experiments

3.1 Machine vision system setups

A typical computer-based machine vision system is illustrated in Fig. 3.1. The fundamental subsystems include lighting source, industrial camera, operation software, and frame structure. One of the distinguishing features compared to the conventional machine vision system is the use of the AI deep-learning module in this study. Our goal is to build an automatic system for the inspection of internal thread nuts on the on-site production line. We have decided to develop our own system platform system. This system will integrate the machine vision software and hardware implemented on the automatic production line.

The open-source software of Python and C will be employed in this integrated system to operate and communicate between various automation platforms and control modules. An optical microscopic system with a pericentric hole inspection lens for acquiring the image of the internal screw nut is shown in Fig. 3.2. The inspection module includes a CCD industrial camera, a pericentric hole inspection lens, a lighting source, and a special design fixture to host the internal screw nut. The fixture is designed to ensure that the position is centered under the optical lens.

In Fig. 3.3, a rotary disc of a fixture system with an angle/degree indicator is depicted to identify the orientation of the internal screw nut. The thread of the internal screw nut has a helical shape and is axis-asymmetric in nature. As regards the misaligned screw nut, the orientation of the tilt angle is considered to be important and must be determined. The rotary disc with the angle/degree indicator will be very useful for this calculation.

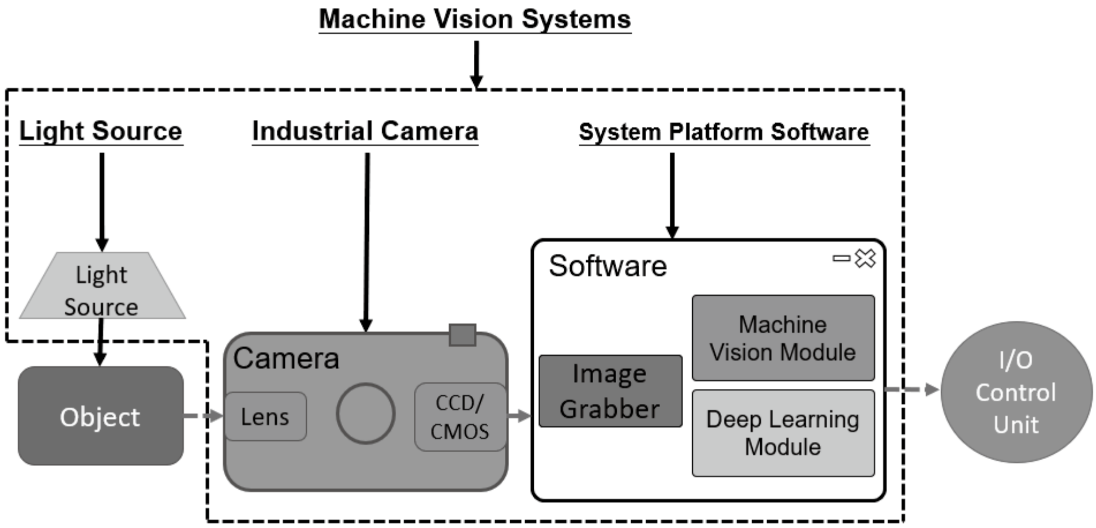


Fig. 3.1 Hardware and software algorithm for the machine vision-based system.

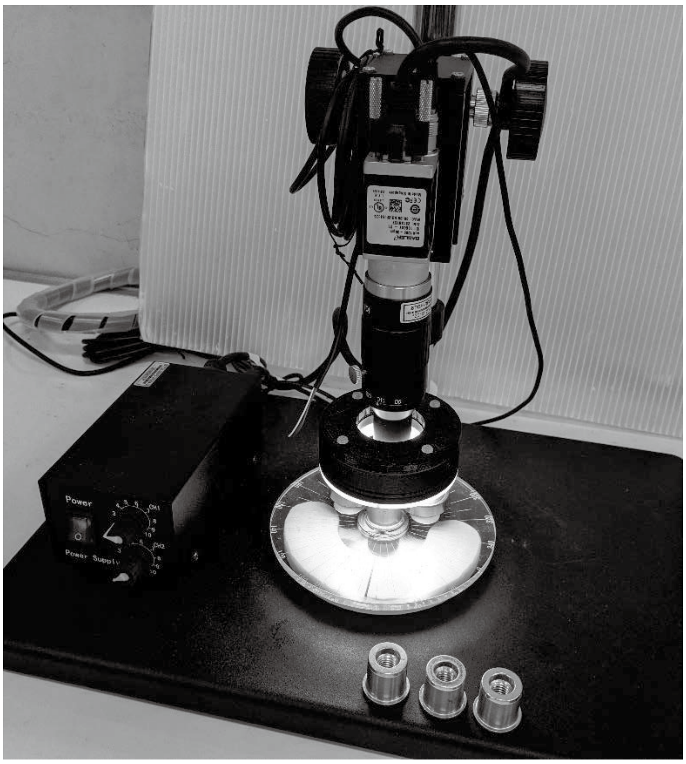


Fig. 3.2 Optical microscopic system with a pericentric hole inspection lens for internal screw nuts.

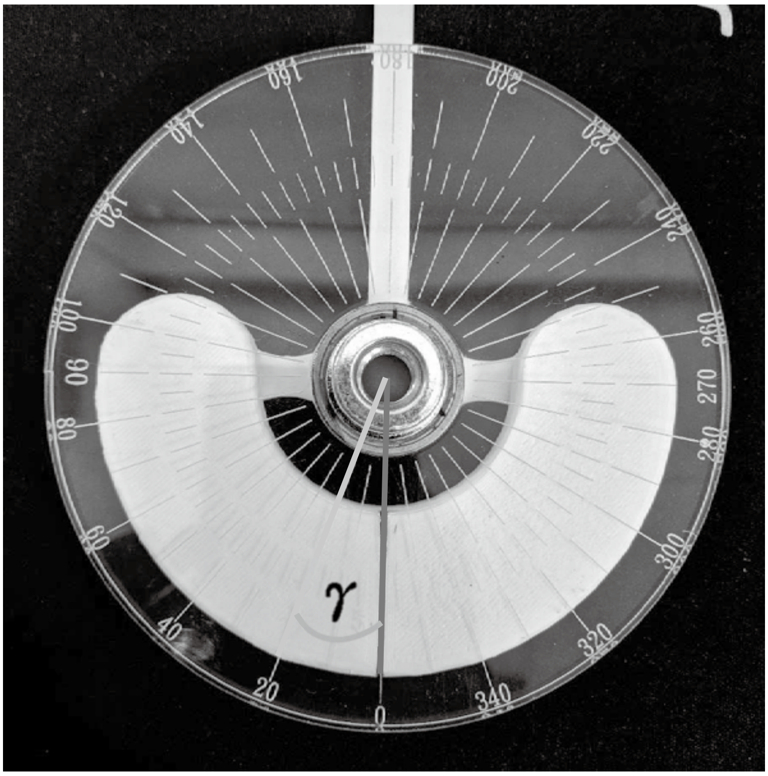


Fig. 3.3 The rotary disc of a fixture system with an angle/degree indicator

3.2 Image capture for internal screw nuts

With the aid of a pericentric hole inspection lens and a computer-based machine vision system, the image of the inner part of internal screw nuts can be obtained easily. Figure 3.4 shows the inner part of a normal internal screw nut in a single 2D image. The capture of the time interval is just a blink, which is well suited for on-site automatic inspection. In this image, the screw height of the internal nut is converted into the screw width of the inner part. The line of thread represents the edge of the thread pitch and is clearly shown in the helical path. In the case of a normal internal screw nut, the line of thread is clear and sharp, and can be categorized into the quality satisfaction class.

On the subject of thread defects and thread misalignment, Figs. 3.5 and 3.6 depict typical and common cases in which internal screw nuts have trouble passing quality control. Figure 3.5 shows an internal screw nut with defects. There are some flaws or scratches on the edge of the internal thread. These small dents and bumps on the thread surface will make the movement of the thread plug gauge difficult during the quality test. Internal screw nuts with these defects should be eliminated.

In order to understand the root cause of misaligned threads, Fig. 3.6 presents an isometric view and a side view of a misaligned screw nut. The centerline of a misaligned screw nut may have an eccentric angle compared with a normal one. If the misaligned angle is very tiny, it may be missed by the current examination method. The tolerance for such misaligned angles in the fastener industry is recommended to be no more than 2 deg as measured from the centerline of the screw nut.

A typical misaligned internal screw nut with a large or obvious tilt angle is shown in Fig.

3.7. In this sample, we can observe that the surface of the thread pitch is in good shape but the line of thread is distorted due to the deviation of the central axis line of the internal screw nut. If the tilt angle is large enough, the imbalance of the thread width can be distinguished easily from the image. In contrast, for a small tilt angle, distinction with the naked eye can be difficult.

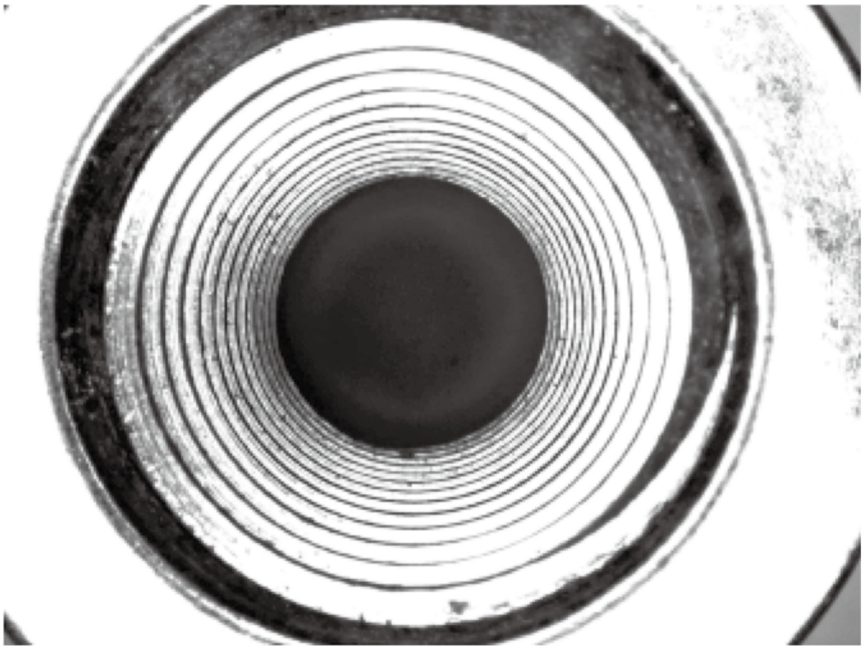
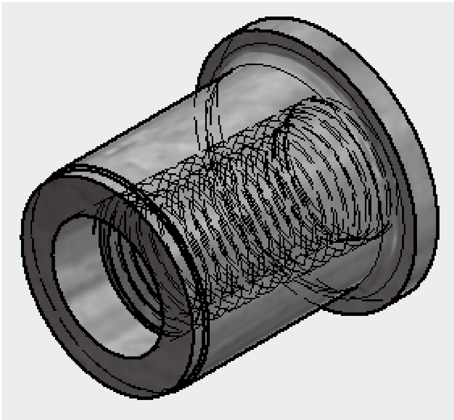


Fig. 3.4 An image of the inner part of a normal internal screw nut.

Fig. 3.5 An image of the inner part of an internal screw nut with defects.



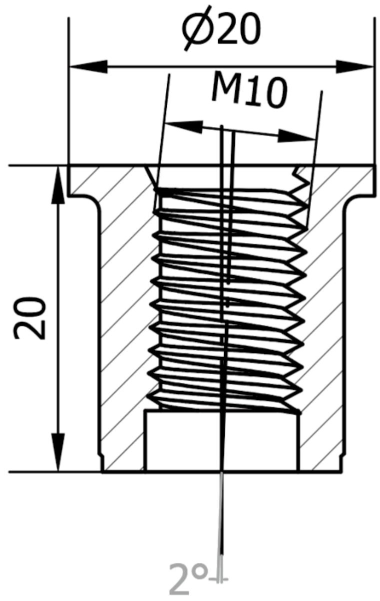


Fig. 3.6 The isometric view and side view of a misaligned screw nut.

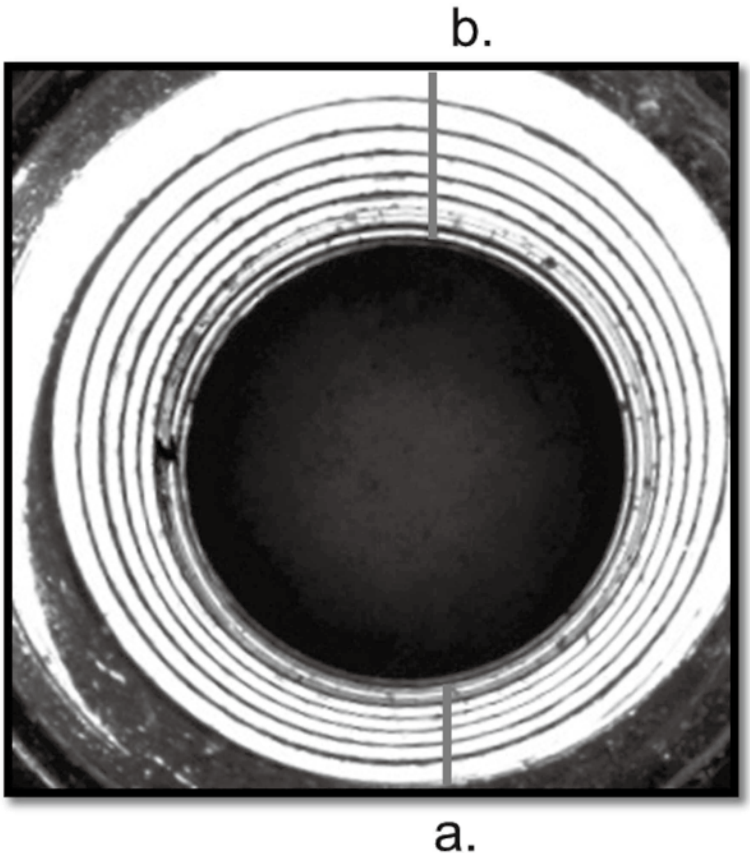


Fig. 3.7 An image of the inner part of an internal screw nut with a misaligned central axis.

4. CNN methodology and customized machine vision system

4.1 CNN methodology

Deep learning refers specifically to a class of algorithm called a neural network. There are also other categories of machine learning, such as unsupervised learning and reinforcement learning. A deep neural network contains a series of fully connected layers and attempts to tune the connection weights until the learning makes sense. A fundamental and detailed introduction to deep learning for engineers can be found on many websites, such as the introduction to Keras for engineers in [10]. Further applications and algorithms can be found in [11-14].

CNNs are composed of a combination of three basic layers: a convolution layer, a pooling layer, and a fully connected layer. The convolution layer and the pooling layer are essential for the feature-extraction processing of an image or graph. The fully connected layer performs the task of object classification based on input from the pooling layer. The convolution layer and the pooling layer may be repeated as many times as needed, depending on the complexity of the input image and the performance of feature extraction. The mathematical operation is, however, much more complicated than we can describe here. Fortunately, a variety of machine learning libraries have emerged to help navigate these mathematical complexities. Some of the most popular machine learning libraries include TensorFlow and Keras.

The crucial steps to using TensorFlow and/or Keras are data loading, data processing, building a model, and training a model. These have been formatted into steps called functions in Python or C programming languages, which handle the complicated calculations of CNN methodology. In this study, the flowchart for the CNN algorithm and training a model is shown in Fig. 4.1. Two object classes are set: "OK" class for normal internal thread nuts and "NG" class for internal thread nuts with defects and/or misaligned tilt angles.

4.2 Model training and customized machine vision system

In order to train a model for use in deep-learning modules, we need to collect relevant images based on the classifications for normal, defective, and misaligned internal screw nuts. Before we start training a model, we need to make these datasets required formats in order to satisfy the performance-critical details of TensorFlow and/or Keras libraries. While training a model, we need to keep track of the performance metrics not only in a training dataset but also in a validation dataset.

Table 4.1 shows the typical internal screw nut images with and without defects we collected for building a training model. For misaligned internal screw nuts, however, it is more complicated due to measurement of the tilt angle and the direction of the tilt angle.

After the training model is realized, a customized machine vision system is developed to serve as a user interface (UI) between the I/O control unit and the deep-learning module program. As mentioned above, our goal is to integrate the on-site automation equipment into this customized machine vision system. More functions are added to this human-friendly UI software, as shown in Fig. 4.2. These function buttons in the UI window include snapshot, inspection-only on, inspection-only off, and image saving. The inspection data can be further analyzed and collected to make statistics relevant to the quality control of this batch of internal screw nuts.

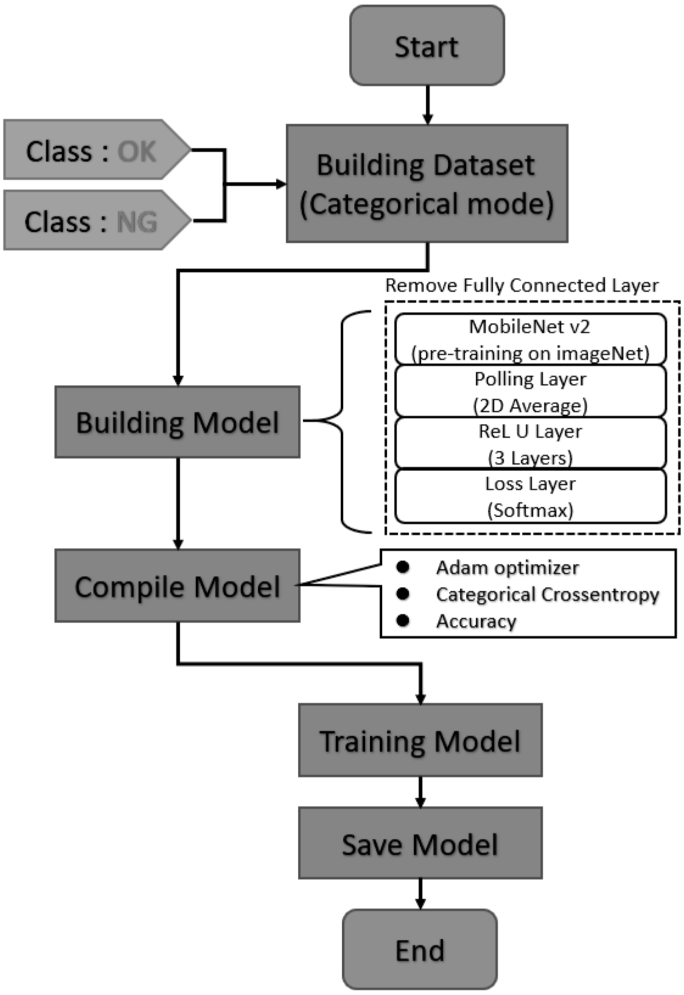


Fig. 4.1 Flowchart for the CNN algorithm and training model. [11]

Table 4.1 Internal screw nut images with and without defects for building a training model.

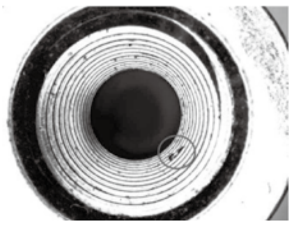
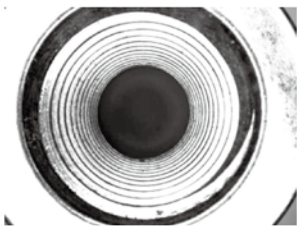
No.	Class	Description	Example
0	NG	internal screw nut with defect	
1	OK	internal screw nut without defect	

Fig. 4.2 User interface of a customized machine vision system.

5. Results and discussion

5.1 Results for internal screw nuts with defects

The performance of the AI recognition for internal screw nuts with defects and misalignment depends on the training model we obtained. The quantity of images for the "OK" class of normal internal screw nuts is 288 pictures, and that for the "NG" class of normal internal screw nuts with defects is 864 pictures. The convergence of the model is based on the criteria of training accuracy to determine the availability of the current model. Fortunately, the training accuracy of the models used in this study is always 100%, thereby satisfying the requirements of convergence.

After the model is obtained from the training processes, it is installed in the customized machine vision platform we developed for the on-site inspection of internal screw nuts. Figures 5.1 and 5.2 show the inspection results for internal screw nuts without and with defects, respectively. For the "normal" internal screw nut, the inspection result shows that the class category is "OK" and the performance metrics is 1. Another extreme inspection result for an internal screw nut with defects is demonstrated in Fig. 5.2, in which the class category is "NG" and the performance metrics is -1.

More inspection results for internal screw nuts with defects are shown in Fig. 5.3, and these results all show obvious flaws or scratches upon careful examination. Performance tests of this AI model are conducted to ensure the inspection ability of internal screw nuts. A total of 121 internal screw nuts were chosen during the inspection performance tests, comprising 117 "normal" and 4 "defective" internal screw nuts. The statistics of the inspection results for "OK" and "NG" classes of internal screw nuts are listed in Table 5.1. The results favorably verify the quality of the current AI training model established in this study.

Fig. 5.1 Inspection results for a normal internal screw nut.

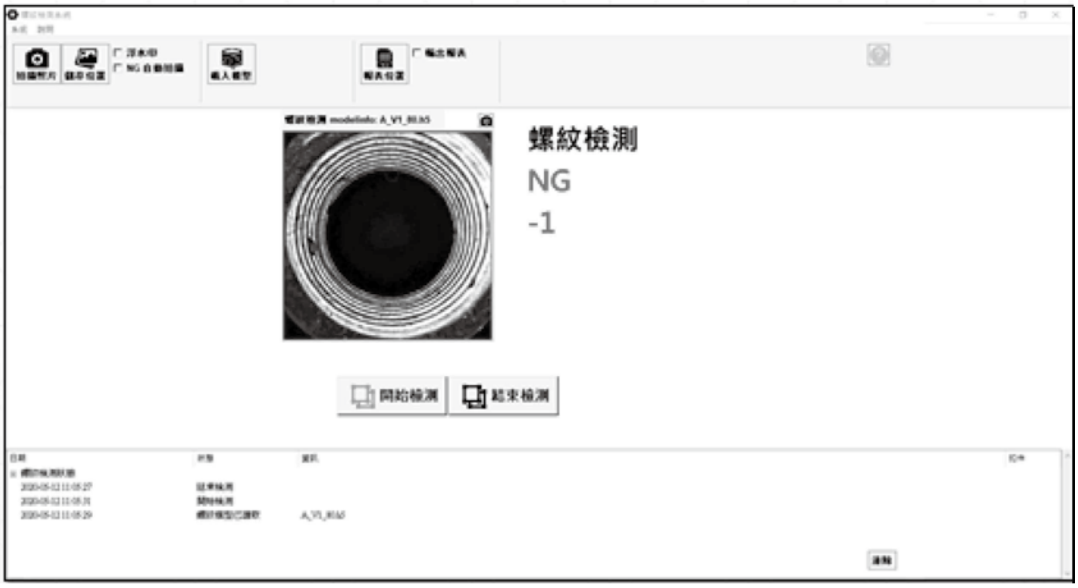


Fig. 5.2 Inspection results for an internal screw nut with defects.

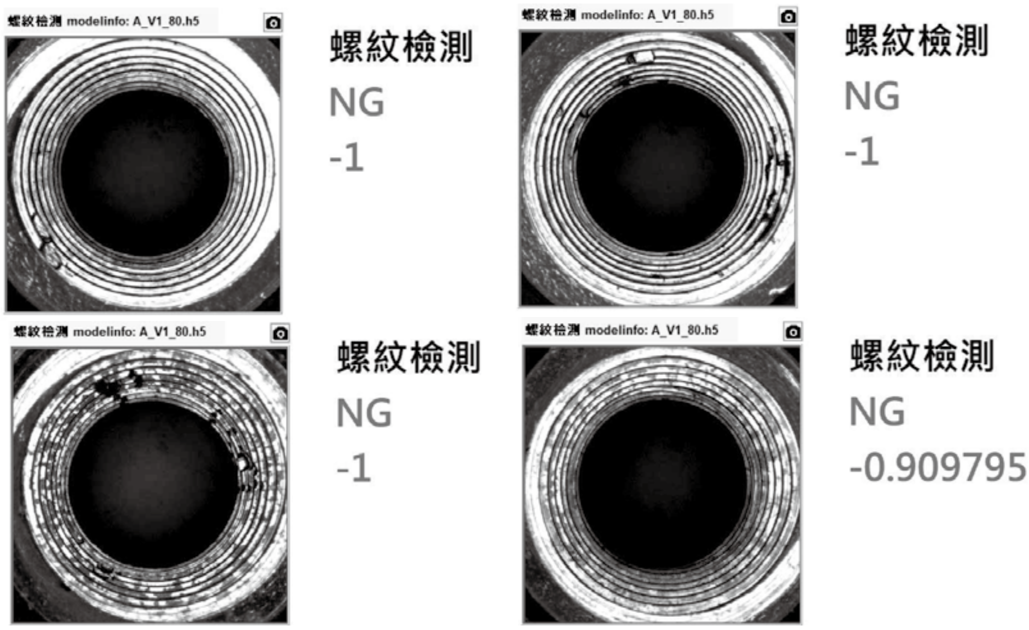


Fig. 5.3 More inspection results for an internal screw nut with defects.

Table 5.1 The statistics of inspection results for the "OK" class of a normal internal screw nut and the "NG" class of an internal screw nut with defects.

Amount of inspections	Class	Percentage	Max. of metrics	Min. of metrics
117	OK	100%	1.0	0.99
4	NG	100%	−0.99	−1.0

5.2 Results for internal screw nuts with misaligned tilt angle

Misaligned internal screw nuts are quite difficult to confirm because the internal threads remain perfect and can easily pass the conventional inspection methods for internal screw nuts, such as the thread plug gauge test. One common way to detect a misaligned tilt angle is using a standard thread plug gauge with a flat flange as a reference plane to measure if there is any clearance when the nuts are turned to the root or the bottom of screw. If the misaligned tilt angle of the internal nut is not very large, then the revealed gap between the nut edge and the plug flange will be quite difficult to detect by visual inspection alone.

The procedures to train the model for misaligned internal screw nuts are similar to those of the defect case. In this study, in order to obtain a significant amount of misaligned internal screw nut samples, an artificial approach to simulate the tilt angle is applied to the thickness gauge to one end of the internal screw nuts. The thickness of the gauge is selected according to the measurement of the tilt angle of misaligned internal screw nuts. These clearance values can be determined from a simple calculation of geometric conversion. The corresponding values for 1 to 8 deg of misaligned tilt angle are 0.18, 0.35, 0.52, 0.7, 0.87, 1.05, 1.23, and 1.4 mm, respectively.

The main characteristic of a misaligned internal screw nut under the pericentric hole inspection lens is the unbalanced thread thickness of captured images, as mentioned in Fig. 3.7. Figure 5.4 shows the inspection results for large misaligned internal screw nuts categorized as "NG" class. The value of performance metrics is determined to be -1. The misaligned tilt angle of Fig. 5.4 is 6 deg and the unbalanced thread thickness is quite obvious and can be observed by the naked eye.

As the misaligned tilt angles become smaller, the unbalanced thread thickness starts to become indistinct. Figure 5.5 depicts an internal screw nut with a moderate misaligned tilt angle at 3 deg. It is difficult to observe any misaligned tilt angle in this case, and it seems almost invisible to the naked eye. Our AI model can detect the difference, however, and the screw nut is categorized as "NG" class.

As expected, for smaller tilt angles, the detection ability of misaligned internal screw nuts gradually deviates from "NG" class. Figure 5.6 shows the inspection results for the 2-deg tilt angle. Although, the inspection results appear to fit the "OK" class, the value of the performance metrics is far from the perfect value of "1," and it can thus be attributed to the "misaligned" class. However, for the 1-deg tilt angle, the current AI training model reaches its detection limit and cannot distinguish the 1-deg-misaligned internal screw nuts. The inspection results are shown in Fig. 5.7.

More samples of misaligned internal screw nuts have been prepared for the inspection tests of various tilt angles. For the current AI-trained model used in the customized machine vision system, the inspection results are shown in Table 5.2 for various tilt angles. The maximum and minimum values of performance metrics are presented in a range of -1 to 1. Based on the results of Table 5.2, the current AI-trained model for misaligned internal screw nuts with a 1-deg tilt angle appears insufficiently sensitive to detect the deviation. For tilt angles more than 2 deg, however, the current AI-trained model can identify the presence of misaligned discrepancies to a great extent. For a better effect, a tilt angle of more than 3 deg is recommended for the current AI-trained model. Therefore, the range of performance metrics for internal screw nuts with misaligned tilt angles and/or defects can be modified according to the performance of inspection tests, as shown in Fig. 5.8.

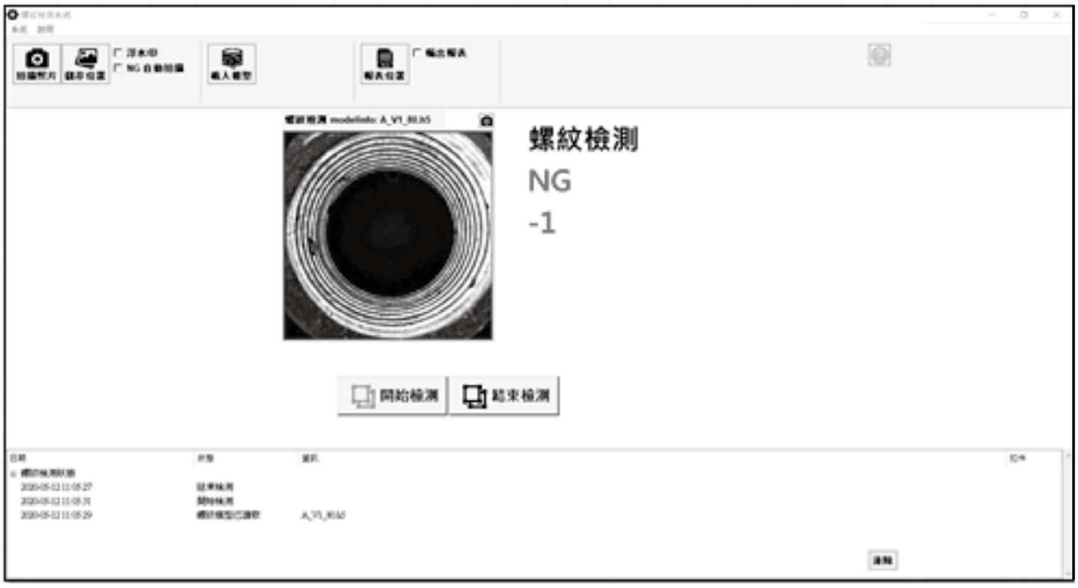


Fig. 5.4 Inspection result for an internal screw nut with a misaligned tilt angle (6-deg angle).

Fig. 5.5 Inspection result for an internal screw nut with a moderately misaligned tilt angle (3-deg angle).

Fig. 5.6 Inspection result for an internal screw nut with a small misaligned tilt angle (2-deg angle).

Fig. 5.7 Inspection result for an internal screw nut with a 1-deg tilt angle.

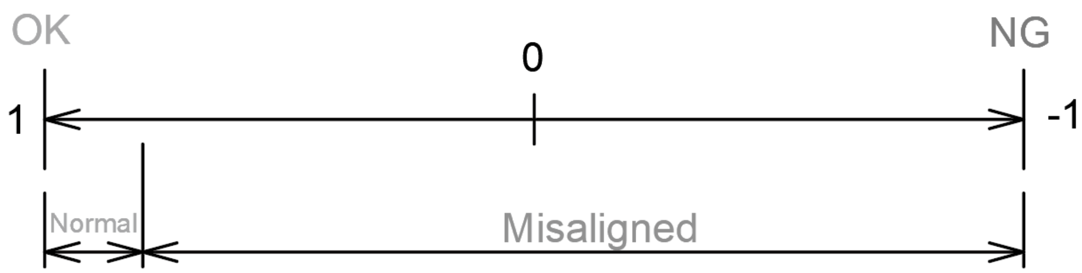


Fig. 5.8 The range of values of performance metrics for internal screw nuts with misaligned tilt angles and/or defects.

Table 5.2 Effect of misaligned tilt angles of internal screw nuts on the values of performance metrics.

Tilt angle	Class	Max. of Metrics	Min. of Metrics	Clearance with respective to flange of plug (mm)
1°	OK	0.99	0.97	0.18
2°	OK	1.0	0.48	0.35
3°	OK/NG	1.0	-0.44	0.52
4°	OK/NG	0.97	-1.0	0.7
5°	NG	0.37	-1.0	0.87
6°	NG	-0.42	-1.0	1.05
7°	NG	-0.99	-1.0	1.23
8°	NG	-1.0	-1.0	1.4

6. Conclusions

In this study, we propose an AI methodology based on a convolution neural network of deep-learning theory for an on-site inspection method of internal screw nuts with defects and/or misaligned tilt angles. The following conclusions are made for further applications:

(1) An optical system with a pericentric hole inspection lens is integrated with a fixture and

is employed to capture the images of the inner parts of internal screw nuts. The helical line of the internal thread is clear and fully visible.

(2) AI models based on CNN methodology are trained and applied to the detection of the flaws or scratches of internal screw nuts. The testing results show the feasibility of on-site inspection.

(3) For internal screw nuts with defects on the surface of the inner thread, the AI-trained model provides 100% assurance of the differentiation between "OK" class and "NG" class.

(4) For the detection of misalignment in internal screw nuts, the detection limit and sensitivity of tilt angles are discussed in this study. A 2-deg angle is the smallest misaligned angle that the current AI-trained model can be effectively triggered.

(5) We found that the values of the performance metrics vary widely with the tilt angles of the misaligned internal screw nuts. This variation may be due to the slant direction of the tilt angle with respect to the starting point of the helical line of the internal thread.

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