Fault Detection of Mechanical Components using Machine Vision

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Abstract -In this paper, an automated system isolates defective bolts from conveyor belts to increase the efficiency and accuracy of detection compared to manual labor. This system consists of a conveyor system, a Raspberry pi development kit, and a high-quality pi camera. The image analysis is carried out using Convolutional Neural Network (CNN) to detect faulty bolts. Bolts that have dimensions outside the standard measurements are labeled as faulty in the proposed system. The prototype fault detection system implemented identifies bolts of various sizes from standards, with an accuracy of nearly 80%, which is a significant achievement.

Keywords: *machine vision, automation system, fault detection, CNN*

I. INTRODUCTION

In the manufacturing industry, defect detection of mechanical components is crucial to maintaining the final product's quality. Thus, detection of faults in mechanical components has become one of the primary concerns. Object detection has many practical applications and also has long been studied through computer vision. Early faulty components detection is beneficial for reducing the emergency repair cost and abrupt failures of products.

A fastener is a piece of hardware that mechanically attaches two or more items. As an example, the mechanical industry uses bolts and nuts as fasteners. Hence, nuts and bolts are essential components of many machines, and they should be in standarad size to facilitate seamless essemble of harware. Before supplying these components (ex: - nuts and bolts) to the industry, it is critical to check the fasteners across standardized values(C. Bharathi Priya, V.Sudha, 2019).

In the manufacturing industry, products move through a conveyor belt from one point to another for packing. In the traditional setting, the quality check is performed during this stage to determine if the component is under suitable conditions. In manual observations, the quality check is carried out visually through random checks. When executing this manually, there is a risk of increasing the human errors as human performance can fluctuate time to time and person to person. This system, which is still in use, is relatively primitive and ineffective. There is a possibility of human errors occurring due to being continuously involved in checking mechanical components. When buyers are compelled to check for fault and non-fault mechanical parts at the purchasing point, the buyers' satisfaction will be lowered. This is a considerable drawback for the mechanical-parts industry.

In this project, detection of faulty components is a functional requirement, and accuracy, efficiency, and time-consuming are the nonfunctional requirements. Therefore, authors have introduced an efficient, secure, machine vision automation system for detecting the mechanical components which can be used in the mechanical component industry more securely. The system proposed utilizes a pi camera, a raspberry pi board, and captured images were examined using a custom-designed image analysis algorithm implemented on a python environment using the OpenCV library.

In this paper, section I deals with the introduction, Section II reviews the current work, the proposed system is explained in section III. Testing and results are discussed in section IV. In section V, a summary of the work is concerned. And finally, section VI discussed future works.

II. RELATED WORKS

Recent works are carried out to detect faulty components using image processing techniques, which could increase effectiveness, accuracy, and time saving. This project makes a huge change in the mechanical-part manufacturing sector and can automatically increase the efficiency of the production line.

Few related works have used single board computers such as raspberry pi to detect objects in the industrial settings. The authors have considered the highest accuracy of detecting the faulty bolts as the performance matric in such systems. Deviating from litearure in the proposed system, authors mainly focus on implementing deeplearning based architures, specifically CNN to improve the fault detection.

Greg et al. utilized machine vision to detect "visual cue" problems in automated assembly line. The test was done on a laboratory conveyor that mimic a three-piece assembly line. Several standard webcams and LabVIEW image processing tool kit created the propsed a machine vision system. The technology's overall usefulness is restricted because it can only detect flaws that were recognized before creating vision systems. Edge detection, pattern matching, Geometric Matching, and Color Inspection are used as image processing techniques (Greg Szkilnyk, Kevin Hughes, Dr. Brian Surgenor, 2011).

MWP Maduranga et al. introduce a novel way to automate the sorting of types of tomatoes supplied in supermarkets of acceptable quality. Color sensors are used to detect the ripeness of tomatoes, where red tomatoes are labeld as ripe and green tomatoes as unripe. The display will reveal whether the tomatoes are ripe or unrip. As a result, tomatoes are categorized automatically based on their color features. Three CCD cameras and an image capture card make up the sorting mechanism. Color images are produced under compact light source. The frame grabber digitizes the analog signal received and gives three user-definable RGB buffers. It consists of a camera and conveyor system. and Image processing algorithms assess whether the tomatoes are ripe enough. (AH Abeykoon, ATK Raweendra, KMJ Perera, TCM Perera, HT Pathirathne, and MWP Maduranga, 2020).

R.T Elster et al. carried out their works on accurately isolating the egg from rest of the objects in an image, while highlighting features of the eggshell, and discriminating between shell fractures and noise. The picture of the egg must be isolated from the rest of the background using image processing techniques to exclude the edge of the egg from the following edge detection method. The backlit image's illumination shows a great contrast between the crack and the rest of the egg. After processing, the backlit image revealed fissures in the form of brilliant streaks. Backlighting generates more contrasted visuals than the front and side lighting. Edge-based thresholding is proven to be more effective at isolating splits than single-line and variable thresholding strategies. The image of the egg must be separated from the rest of the background to exclude the egg's edge from the future edge detection method. They used edge-based thresholding techniques, enhancement, smoothing techniques, contrast stretching, and histogram equalization techniques (R. T. Elster, J. W. Goodrum, 1991).

This paper describes a method for detecting visual faults in empty bottles. The critical constraint is the real-time operation, since the bottles move along the conveyor belt continuously. The authors use the generalized Hough transform to find the position of the bottle in the image. To inspect the bottle's surface, RGB camera obtains photographs of the bottle from various angles at variour posisitons in the conveyor belt. The authors have used three cameras to obtain a distinct perspective on the bottle understudy. The goal is to locate the bottle and take pictures. Real-time object recognition using the Hough transform is employed for this. Once the position of the bottle in the captured image has been determined, to the system inspect the area of interest (in this case the bottle) for any faults. This stage necessitates a thorough examination of every pixel on the bottle (Faisal Shafait, Syed Muhammad Imran, Sven Klette-Matzat, 2004).

Yant et al. proposed an autonomous heliostat problem detection and diagnostic system for solar power facilities that employ machine vision technology and ordinary CCDs (a new method for automatic placement and problem detection of automatic solar heliostats). The vision-based heliostat fault diagnostics system observes the heliostat field with a CCD camera before using image processing to detect damaged heliostats. The proposed system firstly determines the presense of error, and secondly, provide information on where the malfunctioning heliostat is located. Each heliostat is equipped with a hard reflective surface that can track sunlight. In the case that the heliostat fails, sunlight is not reflected on the receiver. To capture the image of the heliostat, a CCD camera is placed adjacent to the receiver. The CCD camera in this system can monitor hundreds of heliostats at once, allowing the system to diagnose hundreds of heliostats with just one camera. This will result in substantial cost savings (Yang Song and Wenjun Huang Xuemei Zhu, 2012).

Limei et al. present a deep convolutional neural network-based technique for detecting micro flaws on the surface of metal screws. Surface damage, surface contamination, and loose screws are among the defects. A visual platform for capturing screw photos was created, and a deep CNN-based approach was employed to detect micro defects on the surface of metal screws. At first image dataset of damaged and healthy helical characters were collected to train deep convolutional neural network (CNN). To achieve effective detection, first, the pixel area of the surface of the screw in the captured image was located. Then the detected screw surface information is feed it into a CNN-based defect detectorThe CNN model is trained on large amounts of defective and non defective data captured using the proposed vision system. In addition, to acquire more abstract and more profound basic properties of the target, a nonlinear approximation of the activation function is applied. (Limei Song, Xinyao Li, Yangang Yang, Xinjun Zhu, Qinghua Guo and Huaidong Yang, 2018).

The prototype proposed in this work is implemented using Single Board Computer (Raspberry Pi) which is a low-cost solution. Also, the research investigates real-time application of ML in a single Board Computer. These are the two main novelities of the proposed prototype.

III. PROPOSED SYSTEM

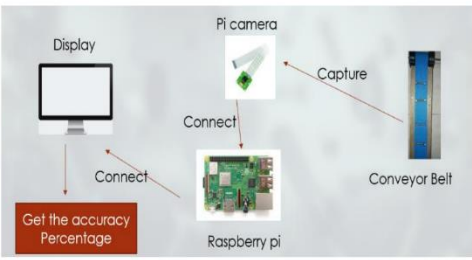

Figure 1. System Overview

A. Hardware Design

In the hardware implmention of the prototype, the conveyor belt moves the bolt from start to finish position. The camera is positioned above the belt, near the exist to capture an image (Camera is positioned as in figure 2) of the belt. These captured images are fed to the processing unit to retrieve the size of the bolt. In this project, faulty bolt are mimiced

by changing the length of the bolt, as the authors could not find an actual defective bolt. Due to this problem, the authors took the two-inch bolt as a standard. If the bolt does not to meet the requirements, the Raspberry Pisends a response signal indicating that the bolt is faulty. This means the faulty nut doesn't satisfy the standard limitations given to the proptotype systeem.

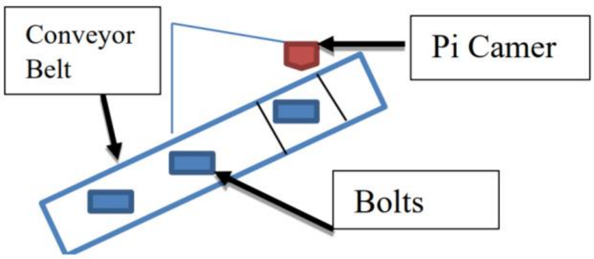

Figure 2. Hardware setup

Finally, the system outputs a summarised results as shown in Figure 3

No of Bolts :
No of Faulty Bolts :
Accuracy Precentage of That Packet:

Figure 3: Display output of PC

B. Software Design

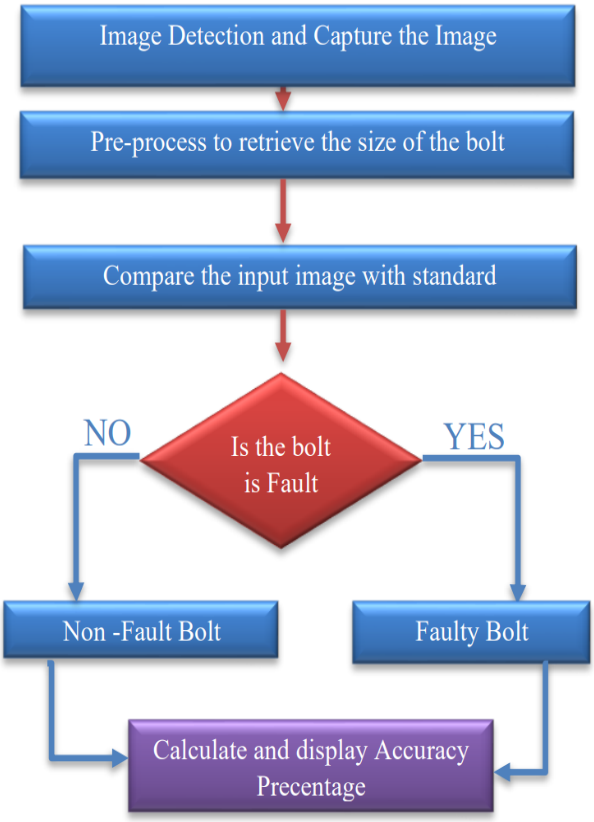

Figure 4 Software Design flow

The proposed system extracts feature and matches features using OpenCV library and TensorFlow package in python. Figure 5 shows a sample image captured by the Pi Came

Figure 5 Captured image of bolt

We have employed CNN (Convolution Neural Network) to detect whether the bolt is faulty or not. Initially, a dataset with 500+ sample images, as shown in Figure 6, is collected to build a dataset of bolts. Then a CNN built using TensorFlow as shown in figure 8 is implemented in python platform to detect the outliers. This trained CNN model with its trained weights is used in the test setup at the deployment

Figure 6 : Data set

C. Hardware Design and Implementation

Figure 7: Designed Conveyor System

The hardware part consists of a conveyor belt system, control system, and pi cam to capture and separate defective ones from bolts. A raspberry pi is used to manage the pi camera. In this design, it has used a fan motor to control the conveyor belt. Further, an on-off switch for stop and start the system was implemented, which separates the faulty and non-fault bolt, depends on the command received from the raspberry pi.

IV. TESTING AND RESULTS

Table 1 sumarise the training and testing accuracy percentage of the prototype. Figure 8 shows a sample output label produced by the prototype.

Table 1. Results of data

Epoch	Accuracy	Val_Loss	Val_Accuracy
5/20	1.0000	2.4347	0.6393
6/20	0.6667	0.6333	0.6657
7/20	0.4444	0.6908	0.4545
8/20	0.5556	0.7909	0.6393
10/20	0.7778	0.5981	0.7214

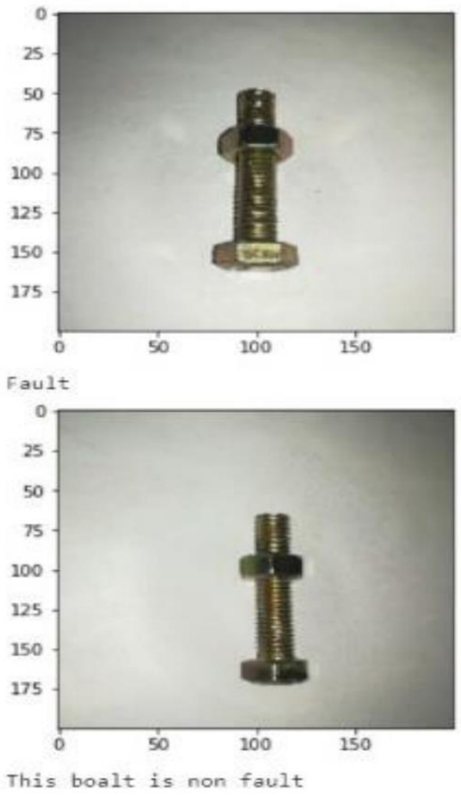

Figure 8: Output of the prototype labelled image

In the 1st trial, CNN is trained and tested with 100 faulty bolts images and 100 non-defective bolts images. When testing the dataset, it identifies 80 bolts as faulty and 110 bolts as non-faulty. Accordingly, the accuracy of identification of defective data percentage is 80%.

In the second trial, above experiment is repeated for the 200 faulty and 200non-faulty bolts. At the testing, CNN identifies 193 no of bolts as defective and 207

bolts as the non-faulty. Accordingly, the model gives 96.5%of accuracy.

Hence, it is concluded that the CNN model trained with less number of data gives low accuracy and a larger dataset would improve the accuracy of the model.

V. CONCLUSION

Authors have successfully designed and implemented a prototype for separating faulty and non-defective bolts in the mechanical industry. Database of faulty and non faulty bolts were created using pi-camera and by changing the length of the bolt. The results shows that the prototyped harware system with CNN modelcan be effectively used for sorting bolts in a manufacuting plant.

VI. FUTURE WORK

As future extention of the work, comparison between other deep learning algorithms, can be carried out. Also, the system could be enhanced such that any mechanical component could be sorted.and parallel sorting supported.

Table 2: Summary of testing Trail

Trail	Fault	Non-Fault	Accuracy (Fault)
Fault – 100 +Non Fault 100	80	110	80%
Fault – 200 +Non Fault 200	193	207	96.5%

REFERENCES

AH Abeykoon, ATK Raweendra, KMJ Perera, TCM Perera, HT Pathirathne, and MWP Maduranga, 2020. Design and Development of A Vision Based Tomato Maturity Detection. 13th KDU International Research Conference.

C. Bharathi Priya, V.Sudha, 2019. Image Processing Based Fault Detection and Isolation for Mechanical Components. International Journal of Engineering and Advanced Technology (IJEAT), pp. 96-98.

Faisal Shafait, Syed Muhammad Imran, Sven Klette-Matzat, 2004. Fault Detection And Localization in Empty Water Bottles Through Machine Vision. E-tech 2004.

Greg Szkilnyk, Kevin Hughes, Dr. Brian Surgenor, 2011. Vision Based Fault Detection of Automated Assembly Equipment. Washington, DC, USA, ASME 2011 International Design Engineering Technical Conferences.

Limei Song, Xinyao Li, Yangang Yang, Xinjun Zhu, Qinghua Guo and Huaidong Yang , 2018. "Detection of Micro-Defects on Metal Screw Surfaces Based on Deep Convolutional Neural Network. Sensors.

R. T. Elster, J. W. Goodrum, 1991. Detection of cracks in eggs using machine vision," Transactions of The ASAE. Volume 34(1), pp. 307 -312.

Yang Song and Wenjun Huang Xuemei Zhu, 2012. Vision-Based Fault Diagnosis System for Heliostats in A Central Receiver Solar Power

Plant. 10th World Congress on Intelligent Control and Automation.

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