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Vision Based Automatic Inspection for Identification of Holes on the Machined Parts

Divya B[1], Kendra N[2], Varshini K R[3], Dr. A. Murugarajan[4]

[1] *Final year UG student, Robotics and Automation, Sri Ramakrishna Engineering College, Coimbatore, Tamil Nadu, India*
[2] *Final year UG student, Robotics and Automation, Sri Ramakrishna Engineering College, Coimbatore, Tamil Nadu, India*
[3] *Final year UG student, Robotics and Automation, Sri Ramakrishna Engineering College, Coimbatore, Tamil Nadu, India*
[4] *Professor, Robotics and Automation, Sri Ramakrishna Engineering College, Coimbatore, Tamil Nadu, India*

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Abstract - Efficiency, quality, and reliability are all dramatically increased by machine vision. The current system checks a sample of randomly chosen products made in huge quantities. This has a significant drawback and a high likelihood of manufacturing faulty goods as well. This study discusses a web-based algorithm for visual inspection that is economical and has several potential uses in real-world scenarios. The optimal algorithm for the vision inspection application is determined by comparing Faster R-CNN and Mask R-CNN in this case.

Key Words: Faster R-CNN, Mask R-CNN, Vision Inspection, Region of Interest, Automatic Inspection.

1. INTRODUCTION

Improved product performance is required by advanced industrial systems, and manufacturing quality control is becoming increasingly important. Defects, such as scratches, stains, or holes on the product's surface, on the other hand, negatively impact the product's performance as well as its appearance and user-friendliness. An effective way to lessen the negative effects of product flaws is through defect detection.

For industrial products, visual inspection is a common technique for performing quality control. Visual inspection is inferior, even though it may be better under some circumstances. For several applications that could result in dangerous repercussions if they failed, visual examination was not an option. Visual inspection falls short of the efficiency and quality standards of contemporary industrial production lines due to flaws such a low sample rate, subpar real-time performance, and low detection confidence. Therefore, it is necessary to create more effective and trustworthy visual inspection methods.

As a result, "Vision Based Robotic Inspection using Soft-Computing" offers the industry a low-cost, effective way to obtain 100% quality assurance. The camera records surface flaws as the components go along the conveyor, makes any necessary drilling in the machined components to check whether they pass, and divides them based on the algorithm's findings. In this paper, we compare the accuracy and speed of the CNN and Masked R-CNN algorithms in real-time with their use in order to determine which algorithm is more accurate and faster.

2. METHODOLOGY

After the Input image has been passed, Convolutional layers are used to train filters to extract the appropriate features of the image. Computation of convolution is done by a sliding filter all along our input image and the result is a two-dimensional matrix called feature map. To decrease the quantity of features in the feature map we use pooling which eliminates pixels with low values. Fully Connected neural network is used to take in input from the RoI Pooling and predict object class and bounding boxes.

Mask R-CNN is developed on top of Faster R-CNN. Network (ResNet, VGG, etc..) is run on input image once and obtains a set of region proposals. Region proposals are regions in feature maps which contain objects. Bounding boxes and object class is predicted. In order to make the prediction of the proposed region fixed size, RoI Align is executed. The last layer Mask head is fed by output of the RoI Align layer, thus forming a mask for each RoI, pixel to pixel manner.

Faster R-CNN

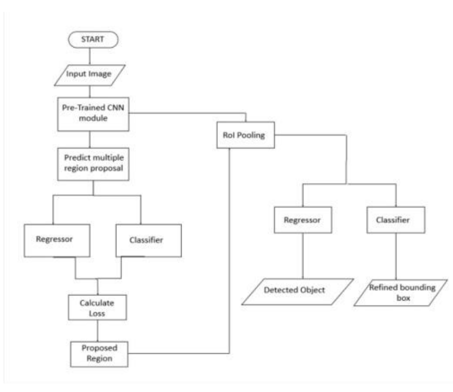

Fig -1: Faster R-CNN flowchart

The RPN is a separate network that takes the extracted feature map as input and generates a set of region proposals, which are potential object locations in the image. The RoI pooling layer extracts a fixed-size feature map from each region proposal and feeds it into a fully connected network. The fully connected network classifies each region proposal as an object or background, and also predicts the bounding box coordinates for the object. The final output of the algorithm is a set of bounding boxes that represent the locations of the hole in the input image, along with their corresponding class labels and confidence scores.

Mask R-CNN

Fig - 2: Mask R-CNN flowchart

The image is uploaded into the Mask R-CNN model. Feature Extraction is done using pre-trained CNN model ResNet50. A set of region proposals is generated which are potential hole locations in the image by taking extracted feature map as input in RPN network. These proposals are generated using anchor boxes, which are fixed-size boxes that are placed at different positions and scales in the feature map. The RoI pooling layer extracts a fixed-size feature map from each region proposal and feeds it into a fully connected network. The fully connected network classifies each region proposal as an object or background, and also predicts the bounding box coordinates for the object. Mask R-CNN predicts a segmentation mask for each object detected in the image. It consists of a small convolutional network that takes the RoI feature map as input and outputs a binary mask that indicates the pixels belonging to the object (holes).

After classification and mask prediction, non-maximum suppression (NMS) is used to remove overlapping region proposals that have a high probability of containing the same object (holes). The final output of the algorithm is a set of bounding boxes that represent the locations of hole in the input image, along with their corresponding class labels, confidence scores, and segmentation masks.

3. MODELLING AND ANALYSIS

Hardware Architecture

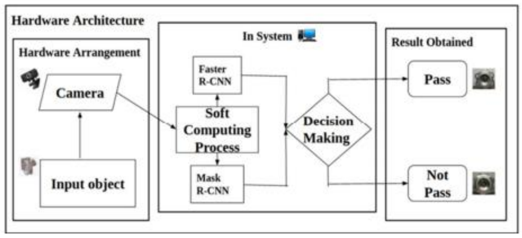

Fig - 3: Hardware Architecture

The proposed methodology of the complete working process involves the hardware and software as mentioned in the above block diagram. Here the input image is directly taken into the processing step in real time with the help of a camera. On the processing side, the image is subjected to two different working algorithms Faster R-CNN and Mask R-CNN, here both of the algorithms work separately and provide their results separately. However the results for both the algorithms are the same (i.e) Pass or Not Pass. Here we compare the Accuracy and Execution Time of each algorithm of each epoch and find which algorithm suits the vision inspection better.

Hardware components required for this set-up:

- Web Camera
- Components to be tested – Fuel for pump housing
- Lighting Source

Software Architecture

Faster R-CNN

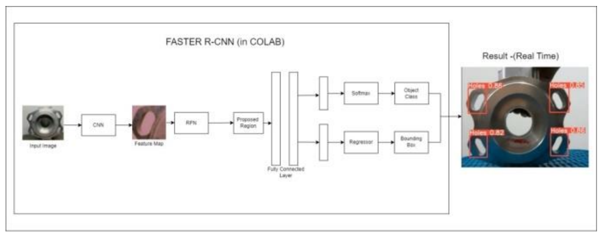

Fig - 4: Software Architecture-Faster R-CNN

First we input images into the Faster R-CNN model. A Convolutional Neural Network (CNN) is used to extract features from the image. Pretrained using pre-trained CNN ResNet50.The RPN is a separate network that takes the extracted feature map as input and generates a set of region proposals, which are potential object locations in the image. The RoI pooling layer extracts a fixed-size feature map from each region proposal and feeds it into a fully connected network. The fully connected network classifies each region proposal as an object or background, and also predicts the bounding box coordinates for the object. The final output of the algorithm is a set of bounding boxes that represent the locations of the hole in the input image, along with their corresponding class labels and confidence scores.

Mask R-CNN

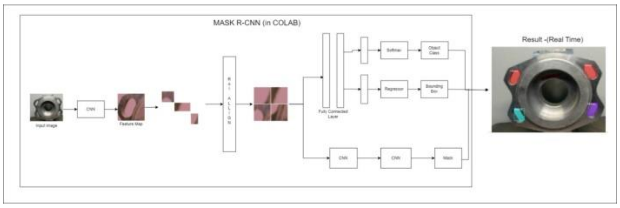

Fig - 5: Software Architecture-Mask R-CNN

The image is uploaded into the Mask R-CNN model. Feature Extraction is done using pre-trained CNN model ResNet50. A set of region proposals is generated which are potential hole locations in the image by taking extracted feature map as input in RPN network. These proposals are generated using anchor boxes, which are fixed-size boxes that are placed at different positions and scales in the feature map. The RoI pooling layer extracts a fixed-size feature map from each region proposal and feeds it into a fully connected network. The fully connected network classifies each region proposal as an object or background, and also predicts the bounding box coordinates for the object. Mask R-CNN predicts a segmentation mask for each object detected in the image. Consists of a small convolutional network that takes the RoI feature map as input and outputs a binary mask that indicates the pixels belonging to the object (holes).After classification and mask prediction, non-maximum suppression (NMS) is used to remove overlapping region proposals that have a high probability of containing the same object (holes). The final output of the algorithm is a set of bounding boxes that represent he locations of hole in the input image, along with their corresponding class labels, confidence scores, and segmentation masks.

Software environments required:

- Google Colab
- RoboFlow

4. RESULTS AND DISSCUSSION

Proposed Environment

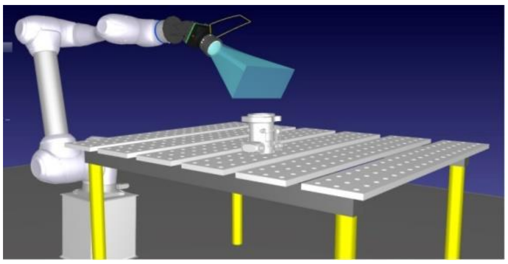

Fig - 6: Proposed Environment

Test results

Faster R-CNN

The testing is done in real time where the object is moved in front of the camera. The result is recorded here. The detection of the object is along with its confidence score which are based upon the input images which is given during the training.

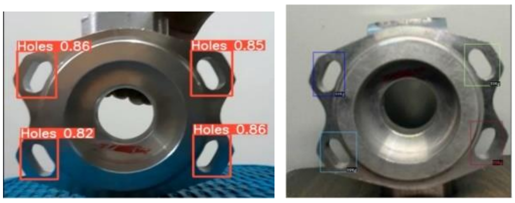

Fig - 7: Real Time Implementation - Faster R-CNN

Mask R-CNN

This is the representation of real time detection using instance segmentation in the Mask R-CNN Algorithm. This is the implementation of a test image while training the algorithm. Here each hole is segmented very well. This indicates the accuracy of image segmentation in Mask R-CNN

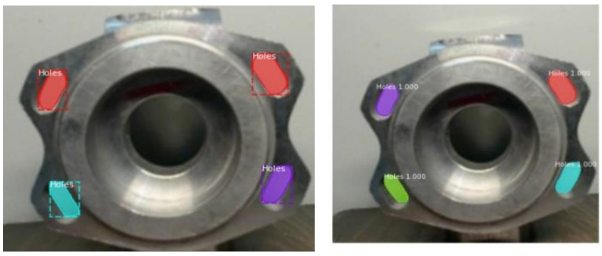

Fig - 8: Real Time Implementation - Mask R-CNN

Comparative Study

For Epoch- 15: Case 1

FEATURES	ALGORITHM	
	FASTER R-CNN	MASK R-CNN
ACCURACY (%)	70	83
EXECUTION TIME (SEC)	90	120

Table - 1: Test result-Comparative Study-Case 1

For Epoch- 30: Case 2

FEATURES	ALGORITHM	
	FASTER R-CNN	MASK R-CNN
ACCURACY (%)	87	90
EXECUTION TIME (SEC)	150	190

Table - 2: Test result-Comparative Study-Case 2

For Epoch- 60: Case 3

FEATURES	ALGORITHM	
	FASTER R-CNN	MASK R-CNN
ACCURACY (%)	91	94
EXECUTION TIME (SEC)	190	300

Table - 3: Test result-Comparative Study-Case 3

For Epoch- 90: Case 4

FEATURES	ALGORITHM	
	FASTER R-CNN	MASK R-CNN
ACCURACY (%)	94	97
EXECUTION TIME (SEC)	200	360

Table 4: Test result-Comparative Study-Case 4

5. CONCLUSION

Both the widely used and successful object detection techniques Faster R-CNN and Mask R-CNN have some significant differences. A two-stage object detection system called Faster R-CNN first suggests regions of interest (RoIs) using a Region Proposal Network (RPN), and then classifies those RoIs using a different classifier. It outperforms earlier object detection techniques in terms of speed and accuracy, but it lacks instance segmentation. By including a third stage that generates segmentation masks for each object instance in addition to object recognition and classification, Mask R-CNN expands upon Faster R-CNN. While it outperforms Faster R-CNN in terms of object detection and instance segmentation, it does so at a higher computational cost.

In conclusion, Faster R-CNN might be a preferable option if only object detection is required because of its quicker inference time. However, Mask R-CNN might be better if you additionally need instance segmentation, even though it has a higher computational cost. We require less complex computation and quicker, more precise predictability during implementation in a production line. Faster RCNN is more appropriate for our application since it predicts more quickly. Mask RCNN takes longer to forecast because it requires complicated calculation. In order to compare the performance of Faster R-CNN and Mask R-CNN, we implemented both in the project's conclusion.

This project claims that Faster R-CNN is the best option for simple and quick calculation for object detection applications.

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