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Surface defects detecting Robot Arm using Machine Learning

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***Abstract* - Identifying defective products is a common problem in manufacturing organizations. They need to segregate these be- fore dispatching to sustain in the competitive market. Industries are trying to segregate defective products by visual inspection which becomes a monotonous and tiring task for every human. To overcome this problem, a robot arm is proposed that could automatically identify surface defects in a product and segregate it if the defect is unacceptable. The Robot Arm uses Machine Learning and Computer Vision to learn from image data of defective and acceptable products. Introducing Robot Arm in the industry will help to identify the defective product in the conveyor line and segregate it from acceptable ones. This would create a competitive advantage for the industry.**

Keywords - Machine Learning, Robot arm, Raspberry Pi, Surface defects, Convolutional Neural Networks

INTRODUCTION

Products produced in the manufacturing plant have to be inspected thoroughly before shipping to market. A product with cracks or any other damage may spoil the reputation of the company and may even face a product liability lawsuit. The defects might be cracks, scratches, design errors, electrical defects, etc. So, to avoid these kinds of circumstances companies implement inspection as a part of quality control. In the Smartphone industry, phones are visually inspected and defective products are found. But defects in the phones are inevitable, defective phones with cracks and scratches may reach the consumers. Visual inspection is not accurate because it is carried out by humans. Also, it is a monotonous and visually tiring process that sometimes causes a human error.

To overcome this error, a robot arm with the help of machine learning can be trained and deployed to identify/detect surface defects or any other damage. Machine Learning algorithms are versatile and can be trained on different image data sets which will lead to a quick, accurate, and efficient way of identifying defects on the surface and segregate defective/non-defective products. The robot arm can be trained to work efficiently than human labor and is compatible with different industries.

In this project, a Convolutional Neural Network algorithm is trained and tested using TensorFlow API. The trained model is then used to find the defects in the product that is captured by a camera. The image is processed using OpenCV to match the input requirements of the model. Finally, the robot arm segregates the product based on the model's prediction.

RELATED WORK

Artificial intelligence is the need of the hour and every operation that we perform today is being influenced by AI in one way or the other. Since its inception, it has helped us in many ways and we too have used AI to make a device that can detect surface defects.

There are several accounts of successful deployment of Surface defects detection systems in the literature. Ya-Hui Tsai, et.al. (2011)[1] in their paper "Surface defect detection of 3D objects using robot vision" present a robot vision system for surface detection of 3D objects taking into consideration the surface reflection and overcoming it by using an image filtering process. An automatic marker-selection process and a template-matching method are then proposed for image registration and anomaly detection in reflection-free images.

Iker Pastor-Lopez, et.al. (2012)[3] in their paper "Machine learning-based surface defect detection and categorization in a high-precision foundry" presented an approach that detects imperfections on the surface using a segmentation method that marks the regions of the casting that may be affected by some of these defects and, then, applies machine-learning techniques to classify the regions in correct or in the different types of faults.

Birender Singh, et.al. (2014)[4] in their paper "Removal of Defective Products Using Robots" proposed a two-step method for removing defective products, finding the defective product with digital image processing, and remove the defective part from the product. The defective product is sorted out based on the threshold value between the real image and the standard image.

Vedanth Narayanan, et.al. (2018)[2] in their paper "Learning Based Anomaly Detection for Industrial Arm Applications" propose an anomaly detection framework for robotic arms in a manufacturing pipeline and integrate it into Robot Operating System (ROS), a middle-ware framework whose variants are being considered for deployment in industrial environments for flexible automation.

In summary, the work that we have presented builds on the research work done previously to emphasize predictive work in our design and manufacturing phase. But we are using the Convolutional Neural Networks algorithm which is proven to have more accuracy and better prediction in image classification tasks. Moreover, the Machine Learning model is integrated with a robot arm to produce a complete and ready-to-use system to be deployed in the industry.

Methodology

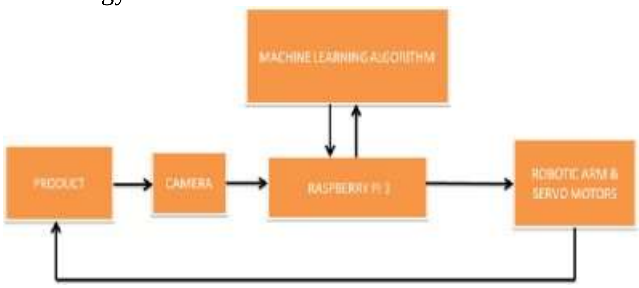

Fig 1
Methodology

- The collected data-set is trained with a 64 filter 2D Convolutional Neural Network implemented using Keras and TensorFlow.
- The trained model is tested and saved in the Raspberry Pi environment.
- The product of interest is captured using Raspberry Pi Camera module and the image is stored in the Raspberry Pi which is fed as input to the trained machine learning model.
- The Machine Learning model predicts whether the product is defective or acceptable.
- If the product is acceptable the Raspberry Pi allows it to pass through the conveyor line. But if the product is defective, it signals the robot arm to pick and place the defective product in the defects section. Thus, the segregation process is completed.

MATERIALS

Robot Arm

The Robot arm proposed for this project is a 5 degrees of freedom robot arm with a mechanical claw as an end effector. The robot arm was designed with SolidWorks CAD modeling software and the necessary STL files were generated for 3D printing the robot arm. Six servo motors are used in the joints of the robot arm including the end effector. The robot arm is connected to the Raspberry pi development board which controls the rotation angle of the servos. The robot arm is easily re-programmable and can be deployed in industry.

RaspberryPi 3

Raspberry Pi is a single-board computer developed by the Raspberry Pi Foundation in the United Kingdom. The model used in this project is Raspberry Pi 3 Model B+ with a RAM of 1GB and external memory (SD card) 16GB. The Raspberry Pi's versatility and multi-functional capabilities make it a natural choice for our project. Moreover, it is cheaper compared to other development boards with the same specifications. Raspberry Pi 3 is used to control the servo motors of the robot arm and also, the trained TensorFlow model is deployed in the Raspberry Pi board. Raspberry Pi's Python code is open source and easy to use.

RaspberryPi Camera Module

The Raspberry Pi Camera module is a Raspberry Pi compatible camera that can be used to take high-definition videos as well as still photographs. A 5MP camera module is used in this project. The camera is connected to Raspberry Pi's Camera Serial Interface (CSI) by a flexible ribbon that has a small circuit board. This camera is used to take the image of the smartphone and to store it in Raspberry Pi.

Collection of Dataset

In this project, we decided to use a smartphone as the product to be inspected. Smartphones with surface cracks on screen were considered defective and those without any surface cracks were considered acceptable. Images of different models of smartphones were collected from Google Images and also, some images were captured by a 48MP camera. 250 images were collected. The collected images consist of both smartphones with surface cracks and without surface cracks. The number of smartphone images with surface defects and without surface defects was equal to avoid bias in prediction. All the images were resized to 750 x 750. The images were converted to .jpg format. After converting, the color of the image was changed to grayscale. The images were then labeled for the training phase of the machine learning process.

The images were labelled as:
Defective product – 0
Non-defective product – 1

Robot Arm Mechanics

Fig. 2
CAD Model of Robot Arm.

A 5 degrees of freedom robot arm is used in this project with a mechanical claw as an end effector. The Robot arm was designed using SolidWorks CAD modeling software (Fig. 2). Finally, it was 3D printed after generating the necessary STL files. The position and orientation of the end effector can be computed for the robot arm by using the Forward Kinematics method. To compute the Forward Kinematics of the robot arm, first, the Denavit and Hartenberg(DH) parameters must be finalized. The Denavit and Hartenberg notation provides a standard methodology to write the kinematic equations of a manipulator. The DH parameters of the robot arm are shown below in Table 1.

TABLE I
DH PARAMETERS

i	$\alpha i-1$A	$ai-1$B	diC	θiD
1	0	60	0	θ_1
2	-90	30	0	θ_2
3	0	120	0	θ_3
4	90	90	0	θ_4
5	90	25	0	θ_5

A The angle about common nor- mal, from the previous (i-1) z axis to new (i) z axis (in degrees).
B Length of the common normal or the radius about previous (i-1) z axis (in mm).
C Offset along previous (i-1) z
axis to the common normal (in mm).
D Angle about previous (i-1) z axis, from previous (i-1) x to new (i) x axis (in degrees).
From the DH parameters the homogeneous transformation matrix from the base to end effector can be computed.

$$^{0}T_1 = \begin{bmatrix} \cos\theta_1 & -\sin\theta_1 & 0 & 60 \\ \sin\theta_1 & \cos\theta_1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

$$^{1}T_2 = \begin{bmatrix} \cos\theta_2 & -\sin\theta_2 & 0 & 30 \\ 0 & 0 & 1 & 0 \\ -\sin\theta_2 & -\cos\theta_2 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

$$^{2}T_3 = \begin{bmatrix} \cos\theta_3 & -\sin\theta_3 & 0 & 120 \\ \sin\theta_3 & \cos\theta_3 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

$$^{3}T_4 = \begin{bmatrix} \cos\theta_4 & -\sin\theta_4 & 0 & 90 \\ 0 & 0 & -1 & 0 \\ \sin\theta_4 & \cos\theta_4 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4)$$

$$^{4}T_5 = \begin{bmatrix} \cos\theta_5 & -\sin\theta_5 & 0 & 25 \\ 0 & 0 & -1 & 0 \\ \sin\theta_5 & \cos\theta_5 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5)$$

$$^{0}T_5 = {}^{0}T_1 * {}^{1}T_2 * {}^{2}T_3 * {}^{3}T_4 * {}^{4}T_5 \quad (6)$$

After subsequent multiplications, the co-ordinates of the end effector are:

$$x = 30 * \cos\theta_1 + 120 * \cos\theta_1 * \cos\theta_2 - 25 * \sin\theta_1 * \sin\theta_4 - 25 * \cos\theta_4 * (\cos\theta_1 * \sin\theta_2 * \sin\theta_3 - \cos\theta_1 * \cos\theta_2 * \cos\theta_3) - 90 * \cos\theta_1 * \sin\theta_2 * \sin\theta_3 + 90 * \cos\theta_1 * \cos\theta_2 * \cos\theta_3 + 60 \quad (7)$$

$$y = 30 * \sin\theta_1 + 120 * \cos\theta_2 * \sin\theta_1 + 25 * \cos\theta_1 * \sin\theta_4 - 25 * \cos\theta_4 * (\sin\theta_1 * \sin\theta_2 * \sin\theta_3 - \cos\theta_2 * \cos\theta_3 * \sin\theta_1) - 90 * \sin\theta_1 * \sin\theta_2 * \sin\theta_3 + 90 * \cos\theta_2 * \cos\theta_3 * \sin\theta_1 \quad (8)$$

$$z = -120 * \sin\theta_2 - 90 * \cos\theta_2 * \sin\theta_3 - 90 * \cos\theta_3 * \sin\theta_2 - 25 * \cos\theta_4 * (\cos\theta_2 * \sin\theta_3 + \cos\theta_3 * \sin\theta_2) \quad (9)$$

The equations 7, 8, 9 provides with the x, y, z co-ordinates of the end effector of the robot arm with respect to its base. Thus the Forward Kinematics of the Robot Arm is computed.

MACHINE LEARNING

Model Selection

After data collection, a suitable machine learning algorithm must be selected. The purpose of this project is to identify the surface cracks from image data and segregate them. The task finally boils down to image classification. Two models were considered for this project - Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN). In a neural network, as the number of layers increases, the number of parameters grows rapidly. This can make training for a model computationally heavy and sometimes not feasible. Tuning so many parameters can be computationally expensive. The tuning time for these parameters is diminished by CNNs. CNN is a fully connected feed-forward neural network and they are very effective in reducing the number of parameters without losing on the quality of models. Therefore, Convolutional Neural Networks (CNN) is selected for this project.

Data Preparation

Before the training of the machine learning model, the data needs to be prepared and cleaned. The labeled image data is first loaded and then converted to grayscale. This speed up the process of training. Moreover, the defects are easily identifiable even in grayscale images. Then the images are resized to fit the model. After these processes, the data-set is ready to be trained.

Model Architecture

The Convolutional Neural Network algorithm is implemented in this project using TensorFlow 2.0 API and Keras.

The model architecture is as follows:

- A 2D Convolutional layer with 64 filters and a stride of (3,3).
- A Rectified Linear Unit (ReLU) activation layer.
- A Pooling layer of size (2,2).

This structure is repeated thrice to extract maximum features from the images and then the following structure is used:

- A Flatten layer.
- A 64 x 1 dense layer.
- A 1 x 1 dense layer with sigmoid activation function.

Finally, the model is compiled with a binary cross-entropy loss function and Adam optimizer.

Training the model

After structuring the model and compiling it, the training stage of the model starts. For training the model, the batch size is set to 32 and the number of epochs (an epoch refers to one cycle through the full training data-set) is set to 10. The collected and pre-processed data-set along with its labels are loaded to the model. An early stopping parameter is also used to stop the training of the model once it exceeds the accuracy of 98%. The model is then tested using the test data-set and custom data. At last, the model is saved to be deployed in the Robot arm using Raspberry Pi.

RESULTS

• The dataset was split into training and test set with 70:30 margin (with 70% training set and 30% test set).
• The data was trained for 10 epochs with the help of TensorFlow and Keras.
• After 10 epochs the accuracy of the model attained 98.5% with a loss of 5%.
• The trained model was then tested with a custom image.
• A non-defective image was used as a test image and the model predicted it correctly, results were positive also with defective images.
• When the model is deployed in Raspberry Pi and integrated with the Robot arm, it correctly identifies the smartphone as defective or acceptable and segregates it as expected.
• Therefore, the trained model is successful in predicting the defective/non-defective products, and also the robot arm carries out the segregation task accurately.

CONCLUSION

Every manufacturing industry strives hard to maintain minimal defective products that are dispatched out of their production facility. This is precisely the reason why a Quality Control/ Inspection department is housed in every industry. But visual inspection is a monotonous and tiring process and there is a high chance that defective products may be labeled as non-defective due to human error. The main objective of this project is to eliminate this error with the help of automation and Artificial Intelligence. The Robot arm that is proposed in this project uses a trained and tested Convolutional Neural Networks algorithm. The training is implemented with the help of image data collected from various sources. After training the accuracy of the algorithm reached 98.5% with a loss of 5%. With such maximum accuracy, the model can be deployed in industries and is assured to perform efficiently. When the model is integrated with the robot arm connected to Raspberry Pi and Camera module, it accurately predicts(defective/non-defective) the smartphone in front of it and segregates it if the smartphone has a cracked display.

The concept can be extended to other surface defects that can be identified visually. The data, in that case, should cover all the defects that are under consideration while at the same time maintaining the defective non-defective image ratio. The robot arm can be easily reconfigured and reprogrammed to suit the needs of the industry in which it is deployed.

REFERENCES

[1] Ya-Hui Tsai, Du-Ming Tsai,Wei-Chen Li,Wei-Yao Chiu, “Surface defect detection of 3D objects using robot vision”,June 2011 Industrial Robot 38(4):381-398.

[2] Vedanth Narayanan, Rakesh B. Bobba, “Learning Based Anomaly Detection for Industrial Arm Applications”, January 2018.

[3] Iker Pastor-Lopez, Igor Santos, Aitor Santamaria-Ibirika, Mikel Salazar, ”Machine learning based surface defect detection and categorization in high-precision foundry”, July 2012, ICIEA.2012.6360934.

[4] Birender Singh, Mahesh Chandra, Nikitha Kandru, ”Removal of Defec- tive Products Using Robots”, AISC Vol 328, 2014.

[5] L. Li, Y. Wu, Y. Ou, Q. Li, Y. Zhou and D. Chen, ”Research on machine learning algorithms and feature extraction for time series”, 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), Montreal, QC, Canada, 2017, pp. 1- 5., doi: 10.1109/PIMRC.2017.8292668.

[6] Yi Wan, Chengwen Wu, ”Fitting and Prediction for Crack Propagation Rate Based on Machine Learning Opyimal Algorithm”, 2009 Interna- tional Conference on E-Learning , E-Business, Enterprise Information Systems, and E-Government.

[7] Mingyu Liu, Chi Fai Cheung, Nicola Senin, Shixiang Wang, Rong Su, and Richard Leach, ”On-machine surface defect detection using light scattering and deep learning”, Journal of the Optical Society of America A, Vol.37, Issue 9, pp.B53-B59(2020).

[8] Je-Kang Park, Bae-Keun Kwon, Jun-Hyub Park, Dong –Joong Kang, ”Machine learning-based imaging system for surface defect inspection”, International Journal of Precision Engineering and Manufacturing - Green Technology volume 3, 2016.