MEKATRONIKA
e-ISSN: 2637-0883
VOL. 5, ISSUE 1, 62 – 66
DOI: https://doi.org/10.15282/mekatronika.v5i1.9408

ORIGINAL ARTICLE

Screw Absence Classification on Aluminum Plate via Features Based Transfer Learning Models

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ABSTRACT – Screw is one of the important elements in every industry. Present of screw play an important role in which it holds the product in its own position and prevent loosen or collision with the case which will cause the small components or compartment fall off from its original position and lead to product failure. With the rise of revolution 4.0 in the industry, it helps to reduce the labor cost and human error. The main purpose of this study is to create a robust classification model used for machine vision detection – absence and present of screw, which could be adapted into respective robotics application system. 6 degree of freedom UR robot, Universal Robot is used to collect the custom dataset in TT Vision Technologies Sdn Bhd. The collected dataset is then classified into two categories, named as absent and present. Pretrained dataset, ImageNet is used to ease the training process in this research. Transfer learning model is used to extract the features which used to feed into different machine learning models. Each machine learning models undergoes hyperparameters tunning to achieve best classification accuracy. Samling ratio of 60:20:20 is used to separate the data in training, validation and testing respectively before fed into different ml models.

ARTICLE HISTORY
Received: 27th Feb 2023
Revised: 2nd April 2023
Accepted: 10th April 2023
Published: 21st April 2023

KEYWORDS
Machine Vision
Transfer Learning
Machine Learning
Hyperparameter Tuning

INTRODUCTION

Industrial 4.0 is continuous automation of traditional manufacturing and industrial practice using modern smart technologies. Industrial 4.0 also refers as Industrial Internet of Things (IIoT) [1] as it is combining physical manufacturing and production with machine learning and transfer learning in creating interconnection between company [2]. The raised of used in robotic arm have effectively used in the production and these changed have change in our daily life, industrial and working environment. It allows the decrease of movement time and obtain a smoother path, this led to less time consumption and energy saving in production [3].

Hash environment with strong wind and sand is used to install wind turbine. X. Yang et al [4] is a thought study on leaf damage image recognition based on deep learning models with transfer learning and ensemble learning classifiers. This dataset comes from drone blade inspections at a wind farm in western China. It consists of 900 images for training (700 error-free and 200 leaf defects) and 450 images for testing (350 error-free and 100 leaf defects). AlexNet, a convolutional neural network model, was used as the proposed model in this study. For better performance, transfer learning and random forest are then integrated into AlexNet as AlexNet-tl-rf. ImageNet is used to pretrain the transfer learning model. Support Vector Machines (SVMs) were used as comparison models to test the effectiveness of the proposed models. In conclusion, AlxNet-tl-rf achieves the best accuracy of 99.33% among other research models.

Unknown crop diseases can lead to losses in the agricultural sector. Proper identification and detection of plant diseases can save farmers from massive losses. Based on the above statement, Sravan et al. [5] presented a study using transfer learning for deep learning-based plant disease classification. This study used an online dataset, the Pflanzendorf database. There are 20,639 images of potatoes, tomatoes, and peppers from 15 different crops. It includes 5 different types of fungal diseases and 2 viral diseases. The proposed work is performed using the ResNet50 pretrained convolutional neural network architecture. The dataset is trained and tested with a sample ratio of 70:30. To sum up, with fine-tuning, the ResNet50 model achieves 99.26% accuracy.

Machine vision technology is widely used in today's production and life. Sheng et al. [6] proposed a study on multi-target localization and pose estimation based on mixed programming of Halcon and C#. It detects the industry used screws by using the mixed programming, it can help in reducing the labor and achieving high effectiveness. Daheng's camera (MER-125-30UC) is used. The image processing undergoes 6 steps which are image collection, image graying, image filtering, image segmentation, image morphology and lastly target localization and pose estimation. The operator

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open_framegrabber () is called from the Halcon to set the relevant parameters and grab_image () is called to target the image. In image graying process the collected RGB image is converted into grayscale image by calling the rgb1_to_gray () operator. As for image segmentation, the operator threshold () is called and the operator select_shape is used to select the targeted area. The operator closing_circle () is used to performs the closing operation in the image morphology section. The last section will be the target localization and pose estimation where shape_trans () operator is called to transform the extracted terget area into ellipse and operator elliptic_axis () is called to find the radians of the ellipse relative to the horizontal line, and counterclockwise to the position direction. C# is used as the programming tool to design the simple interface for the study and run on the .NET Core platform. The contribution of this study is it achieves the target recognition, location and pose estimation relatively accurate.

It has been observed from different study, there are few studies which used robotic arm to as the study equipment which related to machine vision. Therefore, the focus of this research is to observe the screw absence detection via features-based transfer learning models and to evaluate different machine learning models in classification accuracy.

METHODOLOGY

A 6 degree of freedom Universal Robot, UR robotic arm is used to collect the required dataset. The collected dataset is divided into two different classes which are the absence and present of the screw. The collected dataset is then transformed into relevant information through the pre-processing methods. The datasets which are features extracted is then fed into different machine learning models which act as a classifier. The performance of the transfer learning models is then analyzed and compared to get the best classification accuracy.

DATA

A total of 200 datasets is collected using the 6 degree of freedom Universal Robot, UR robot robotic arm. The data consist of two different classes respectively which are absent and present.

Figure 1. Screw Image – Present

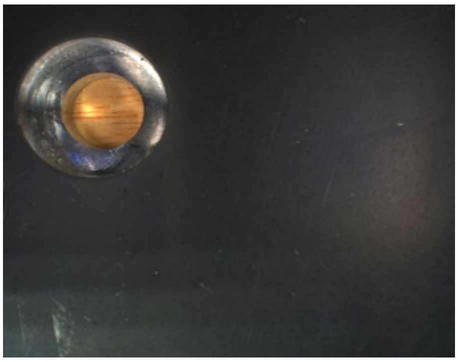

Figure 2. Screw Image – Absent

EXPERIMENT SETUP

Dataset used in this research is collected from Blackfly S Gige camera, which is attached at the end effector of the 6 degree of freedom UR Collaborative Robotic Arm, UR5e. An aluminum plate is place on a flat surface with sufficient lighting background. The screw on the surface is removed to imitate the screw absentee while the screw is then screw screwed into it to imitate the present of screw. The processed is repeated to ensure 200 dataset is collected respectively.

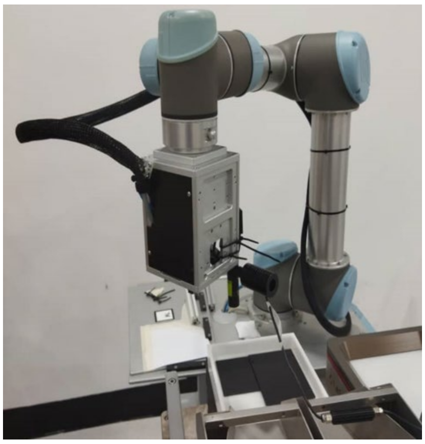

Figure 3. Robotic Machine System, TT Vision technologies Sdn Bhd.

Figure 4. Blackfly S Gige camera, BFS-PGE-50S5C-C

DATA PREPROCESSING, FEATURE EXTRACTION AND SELECTION

A well-known data labelling tool is used for this research which are roboflow. The collected datasets are then labelled manually with a bounding box which are “absent” and “present”. The images are then resized into different resolution to ensure the images is able to fit into different transfer learning model. Transfer learning models is used as the feature extraction method. The extracted features are then trained in traditional machine learning model to get the classification accuracy.

CLASSIFICATION

In the realm of machine learning, transfer learning models are commonly employed to examine how the features extracted from these models influence the learning process. By leveraging existing models and reusing their learned features, researchers can accelerate the development of new tasks [7], [8]. Traditional machine learning models, such as decision trees, support vector machines, or random forests, are then utilized to investigate the impact of these extracted features on the new tasks at hand.

To assess the performance of the machine learning models, it is standard practice to split the available data into three sets: training, validation, and testing. In this study, a sample ratio of 60:20:20 is used to divide the 200 datasets. This means that 60% of the data is allocated for training the models, 20% for validating and fine-tuning their hyperparameters, and the remaining 20% for final testing and evaluation. This division ensures that the models are trained on a substantial dataset, validated on separate data to optimize their performance, and tested on unseen samples to assess their generalization ability.

The evaluation of the machine learning models primarily involves two important metrics: classification accuracy and the confusion matrix. Classification accuracy measures the overall correctness of the models' predictions by calculating the ratio of correctly classified instances to the total number of instances in the test set. It provides an indication of how well the models have learned the underlying patterns in the data and can make accurate predictions. The confusion matrix offers a more detailed analysis of the models' performance, displaying the counts of true positives, true negatives, false positives, and false negatives for each class. This matrix helps identify specific classes that may pose challenges for accurate classification, enabling researchers to gain insights into the strengths and weaknesses of the models. By considering both classification accuracy and the confusion matrix, researchers can thoroughly evaluate and compare the performance of traditional machine learning models when applied to the features extracted from transfer learning models.

RESULTS AND DISCUSSION

The findings depicted in Figure 5, which showcases the bar chart for Transfer Learning Models with Random Forest Classifiers, reveal interesting insights regarding the performance of different transfer learning models. Notably, the Xception transfer learning model stands out from the rest, displaying the highest score across all three training, validation, and testing phases. With a remarkable 100% score in all three stages, the Xception model demonstrates exceptional accuracy and generalization capability. This outcome raises intriguing questions about the specific characteristics and architectural design of the Xception model that contribute to its superior performance compared to other transfer learning models.

The success of the Xception transfer learning model with random forest classifiers warrants further investigation into the underlying reasons behind its outstanding results. One potential explanation could be the unique feature extraction capabilities of the Xception model [9]. Designed with a deep convolutional neural network architecture, Xception is known for its ability to capture intricate patterns and fine-grained details within images. By utilizing these rich features during training, the Xception model might have gained a deep understanding of the dataset, enabling it to make highly accurate predictions during the subsequent validation and testing stages. Additionally, the random forest classifier, known for its robustness and ability to handle high-dimensional data, could have effectively leveraged the extracted features from the Xception model, further enhancing its performance.

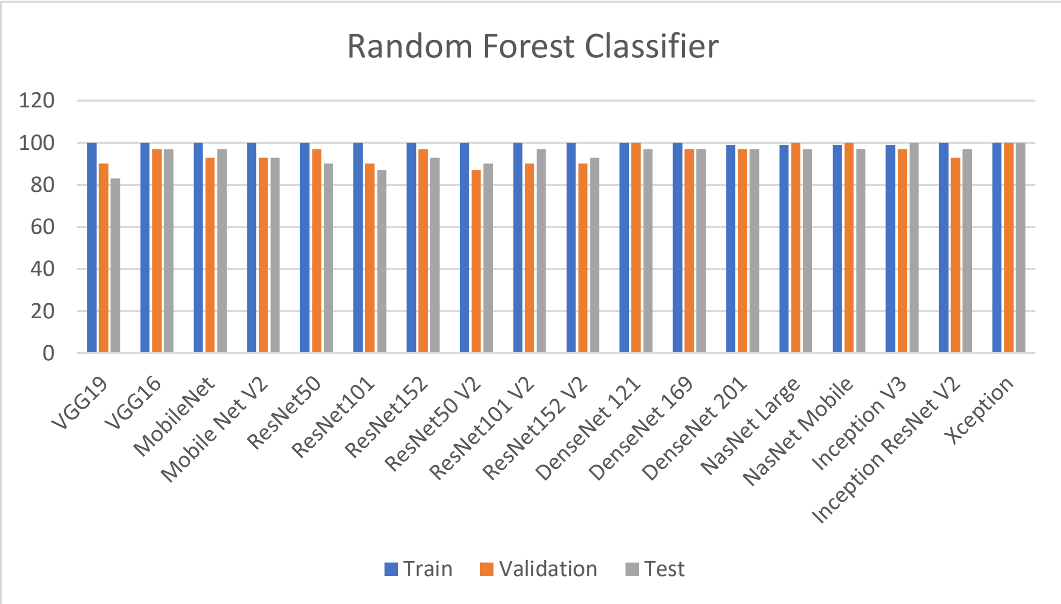

Figure 5. Various Transfer Learning Models with Random Forest Classifier

CONCLUSION

In the conducted study, the raw dataset acquired from the 6 degree of freedom Universal Robot underwent a crucial pre-processing stage. This stage aimed to transform the raw data into a format that could be effectively utilized by the transfer learning models. Pre-processing techniques such as data cleaning, normalization, and feature scaling were employed to ensure that the dataset contained only the relevant and meaningful information necessary for the subsequent analysis. By carefully preparing the data, it was ensured that the transfer learning models would receive high-quality inputs, enabling them to effectively learn and extract valuable features.

The extracted features obtained from the pre-processed dataset were then utilized to train and evaluate various machine learning models. This approach allowed for a comprehensive assessment of the performance and classification accuracy of different models. To determine the best-performing model, the results obtained from the different machine learning models were compared with each other and evaluated against the set benchmarks. Additionally, the employment of a filter-based method can reduce the computational cost of the models. The results of this study demonstrated that the Xception transfer learning model combined with a random forest classifier achieved the highest accuracy, with a remarkable 100% score across all training, validation, and testing phase.

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ACKNOWLEDGEMENT

The authors would like to thank Universiti Malaysia Pahang for funding this work under the grants of RDU202406 and UIC200817.

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