Improving Water Tap Production Lines: A Proof of Concept for Deep Learning-Based Defect Detection System Development

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ABSTRACT

This paper presents the development of a deep learning model designed to identify two classes of object images: the work-in-process of a certain copper-based alloy water tap. The dataset consisted of 316 images of good parts and 320 images of defective parts. Both classes of images underwent processing using oversampling techniques for data augmentation to increase the number of images to 1,000 images per class, before transformation. Subsequently, the processed data were used to train six transfer learning models, including ResNet50, MobileNet, Xception, InceptionV3, EfficientNetB0, and DenseNet121. The results demonstrate 100% accuracy, precision, recall, and F1-score for ResNet50 and EfficientNetB0 when evaluated on the validation and test sets. However, considering the size of the models, it was found that EfficientNetB0 is only 15.48 MB, whereas ResNet50 is 90.03 MB. Therefore, EfficientNetB0 emerges as the optimal deep learning model for the development of an automatic detection and rejection station in the production line of water tap manufacturers in the future. One of the contributions of this study is providing proof of concept for using image processing and deep learning to enhance productivity within a manufacturing environment.

Keywords: Oversampling, Data augmentation, ResNet50, MobileNet, Xception, Transfer learning, Deep learning

INTRODUCTION

A. Background and Significance

Water taps, typically made from copper-based alloys, are fixtures found in every household and building. As a result, they are a daily necessity, used in the morning and before bedtime. This underscores the significance of the tap industry. However, the production of each type of water tap involves over ten steps, such as forging, machining, boring, and assembly. Prior to the final stage of producing finished goods, there is a possibility that the output of each step, known as work-in-process (WIP), may include defective products. These defective pieces must be identified and rejected before proceeding to subsequent stages.

One of the important steps in producing water taps is forging, which results in the output shown in Figure 1. When the part depicted in Figure 1(a), which is a defect part, moves to the next stage for trimming, where excess material is removed from the main part, time and energy are wasted, affecting the productivity of the entire production line. Detecting defects before advancing to the trimming process is crucial to avoid these inefficiencies. Employing image processing and artificial intelligence (AI) to spot defects beforehand holds promise for enhancing overall equipment effectiveness (OEE) [1]. Hence, this study aimed to demonstrate the feasibility of a high-performance model capable of distinguishing between good and defective work-in-progress (WIP). The goal is to showcase the potential of implementing a new system that can enhance production line productivity using the most effective model available.

(a) (b)

Fig. 1. (a) defect with the clipped part and (b) good work-in-process products

A significant achievement of this research is the development of a deep learning model, which can be utilized to establish an automated system for identifying and eliminating defects prior to production in subsequent processes. This initiative aims to ultimately enhance productivity.

This paper expands upon the content of [2]. Following the subsection of this introduction, the paper delves into sections covering image processing overview, deep learning, transfer learning, and related work. Section II outlines the methods employed in the study, while Section III discusses the results and provides analysis. The conclusion and suggestions for future work are presented in Section IV.

B. Image Processing Overview

The manipulation of digital images to extract vital information is commonly known as "image processing" or "digital image processing" [2-3]. Various strategies are employed within this field to tackle specific challenges such as noise generation and signal distortion. Digital image processing proves highly beneficial in addressing image-based issues. Moreover, image processing extends its application into more intricate domains like computer graphics and computer vision technologies, transcending mere data extraction [3-4]. Within digital picture editing, there exist several subfields [4-5] that fall under the umbrella of image processing. These subfields include segmentation, feature extraction and selection, compression and image enhancement, and restoration.

C. Deep Learning and Transfer Learning Overview

Artificial intelligence (AI) has been defined by Gartner as the application of sophisticated analysis and logic-driven methods, such as machine learning (ML), to understand events, aid decision-making, and automate actions. This definition aligns with the current and evolving landscape of AI technologies and capabilities [6]. Machine learning (ML) includes a subset known as deep learning, and both fall under the umbrella of artificial intelligence (AI). These fields draw inspiration from the structure of the human brain. Deep learning involves a technique called transfer learning, where features learned by training a primary network on one dataset can be transferred to a secondary network trained on another dataset [7-8].

This method enhances performance and decreases training time for the expected task by leveraging insights acquired from initial training. Pre-trained models are favored in computer vision and natural language processing for their efficacy and superior performance in analogous tasks. Transfer learning stands out as a valuable optimization approach. Compared to training from the ground up, employing a pre-trained model yields better initial values, gradient steepness, and overall performance.

Inductive, transductive, and unsupervised learning represent some of the classification criteria utilized in transfer learning, aiding in the further categorization of transfer learning scenarios [9]. In this study, six inductive transfer learning models are employed: ResNet50, MobileNet, Xception, InceptionV3, EfficientNetB0, and DenseNet121 as follows:

• ResNet50 [8]: abbreviated from Residual Network with 50 layers, is renowned for its unique residual connections, also known as skip connections, aimed at mitigating the problem of vanishing gradients during training. By integrating skip connections, ResNet50 enhances gradient flow, enabling the network to discern alterations between layers more effectively. This facilitates the capture of intricate characteristics and patterns within the data.

• MobileNet [10]: is a deep learning architecture designed to deliver efficient and robust performance on mobile devices. It employs a method known as depthwise separable convolutions, which involves two distinct stages: depthwise convolutions and pointwise convolutions. This approach divides the computation process, reducing both the required calculations and the model's complexity, all while preserving remarkable accuracy.

• Xception [11]: abbreviated from "Extreme Inception," represents an advanced deep learning architecture. It employs depthwise separable convolutions, which improve the model's capacity to comprehend spatial and channel-wise relationships within data. Unlike traditional convolutional layers that process filters across all input channels, Xception resolves this inefficiency by splitting the process into two separate stages: depthwise convolutions and pointwise convolutions.

• InceptionV3 [12]: is a renowned deep learning model celebrated for its precision in the realm of computer vision. Its architecture relies on a technique involving multi-scale convolutions for feature extraction. Utilizing numerous convolutional layers with diverse kernel sizes simultaneously, InceptionV3 captures features across different scales and resolutions. This diverse convolutional approach significantly enhances its ability to accurately identify intricate patterns and objects in images.

• EfficientNetB0 [13]: is a deep learning model engineered to find an optimal equilibrium between computational efficiency and model effectiveness. Its design incorporates a scaling methodology aimed at refining model size and capability. This architecture operates with three key scaling factors: depth, width, and resolution. Depth scaling entails the addition of more layers to the network, facilitating the capture of intricate features. Width scaling amplifies the number of channels or filters within each layer, thereby improving feature representation. Additionally, resolution scaling adapts the input image resolution to accommodate various data types.

• DenseNet121 [14], [15]: is a sophisticated deep learning model known for its efficiency and robust performance in computer vision tasks. Unlike conventional deep neural networks structured with densely connected convolutional layers (DenseNet), DenseNet121 employs a distinctive approach in layer connection, facilitating direct information sharing among all preceding layers. This unique connectivity enhances feature reuse, thereby mitigating the potential loss of critical information as data traverses through the network.

D. Data augmentation

Data augmentation is a crucial technique in deep learning. It involves artificially expanding a training dataset by applying various transformations to the original data [16]. This process increases the dataset's diversity, enhancing the model's ability to generalize and become more robust [17]. In image processing, data augmentation is usually referred to as image data augmentation or simply image augmentation. Its primary objective is to create new images that resemble the original ones but with subtle differences, which can help improve the accuracy and robustness of deep learning and/or machine learning models [18]. Image augmentation directly addresses the limitations of the dataset, helping prevent overfitting and improving model performance, particularly when training data is insufficient [19]. Common or traditional techniques include rotation, shifting, flipping, resizing, warping, cropping, modifying colors and contrasts, and adding noise (e.g., Gaussian and Poisson) [20-21].

E. Related Research Works

After conducting a survey, numerous interesting previous studies were discovered, including those referenced in [22] and [23] that studied in Thailand. However, as outlined in Table I [24-32], only selected prior works connected to pertinent terms such as deep learning, classification, transfer learning, and manufacturing were identified. Nevertheless, there is a notable absence of research pertaining to Work in Progress (WIP) objects similar to the WIP products discussed in this investigation. Consequently, this presents a potential research gap that motivates the pursuit of the study.

TABLE I. RELATED RESEARCH WORKS

Ref.	Year	Major Issue	*Image Augmentation*	Learning Model						
				ResNet	MobileNet	Xception	Inception	EfficientNet	DenseNet	Others
[24]	2021	Fine-tuned Xception to classify images into 200 classes is presented using the standard Tiny ImageNet dataset	✓	-	-	✓	-	-	-	-
[25]	2021	Using deep learning techniques to empower high-performance visual	✓	✓	-	-	-	✓	-	✓

Ref.	Year	Major Issue	Image Augmentation	Learning Model						
				ResNet	MobileNet	Xception	Inception	EfficientNet	DenseNet	Others
		recognition models can benefit the automation of garbage classification task								
[26]	2021	Intelligent garbage classification system based on deep learning and an embedded Linux system	-	✓	✓	-	✓	-	✓	✓
[27]	2022	Automated recyclable transparent plastic bottle classification system	✓	✓	-	✓	✓	-	✓	✓
[28]	2022	Find a method for identifying the abnormal conditions of fused magnesium furnaces based on deep learning and multi-information fusion	✓	-	-	-	-	-	-	✓
[29]	2022	Recognize the pavement texture using deep learning approaches	✓	-	-	-	-	-	✓	✓
[30]	2023	Achieve efficient Automatic License Plate Recognition (ALPR)	✓	-	✓	-	-	-	-	✓
[31]	2023	Hardness classification method for bearing rings.	-	-	✓	-	-	-	-	-
[32]	2023	Style classification for footwear industry	-	-	-	-	-	-	-	✓

METHODS

To achieve the objective of this study, which is to identify the most suitable model for implementing a new system capable of detecting and rejecting defects in work-in-process products in the future, a methodology involving multiple steps, as depicted in Figure 2, was carried out as follows:

1.1 Image collection: concentrating on a specific type of water tap as outlined in Section I, both the positives and negatives were documented through photography. This study encompasses 316 images of the good work-in-process products and 320 images of the defective work-in-process products.

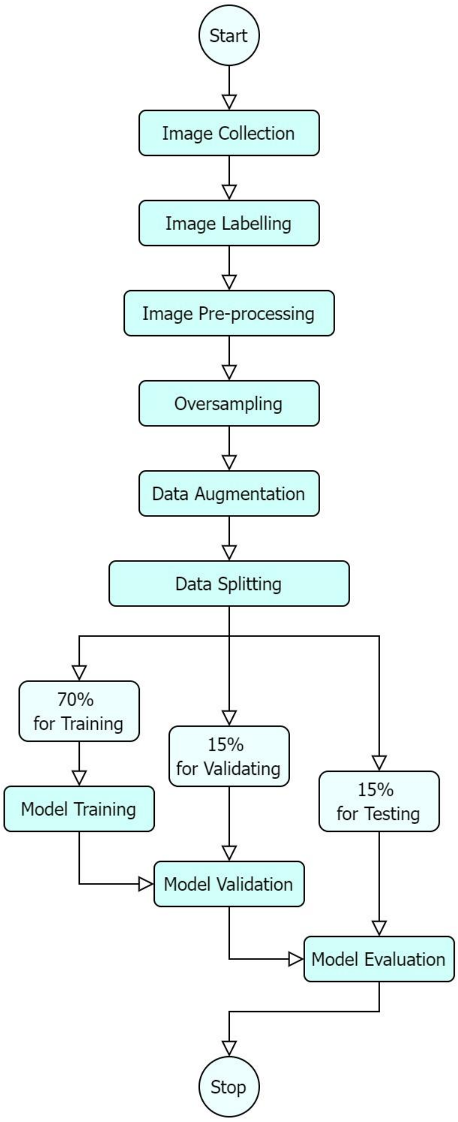

Fig. 3. Diagram of all work processes.

1.2 Image labelling: the images of the good parts and the defective parts were the raw data of two classes called 'good-WIP' and 'bad-WIP' before processing in the next steps.

1.3 Image pre-processing: during this step, cropping and segmentation techniques were employed to standardize the acquired images. This involved ensuring that all images had a 1:1 aspect ratio and a size of 224 by 224 pixels. The uniform cropping effectively corrected the initial asymmetry by encompassing both the upper and lower sections.

1.4 Data Augmentation: in this study, both the 'good-WIP' and 'bad-WIP' classes contained nearly equal numbers of images. However, having only around 300 images for each class might seem insufficient. Consequently, both classes underwent oversampling, a technique within the augmentation process, to boost the number of images per class to 1,000. This was achieved by employing various methods associated with geometric modification, such as rotation and flipping (refer to Fig. 3). The tool utilized for this process is the ImageDataGenerator class in the TensorFlow library in Python, which has been widely used in prior works (e.g., [33-34]). The resulting dataset is referred to as the augmented dataset.

1.5 Data Splitting: in this step, the augmented dataset was partitioned into three separate subsets: a training set (70%), a validation set (15%), and a testing set (15%). The testing set was specifically reserved for model evaluation in the final step.

1.6 Model Training: in this step, six transfer learning models, as delineated in the preceding section, were utilized in this investigation. Each model underwent training using the training set (70%) acquired from the previous stage.

1.7 Model Validation: all trained models underwent validation to ensure their accuracy, utilizing a validation set comprising 15% of the image data during this stage.

1.8 Model Evaluation: this final step is called model evaluation, it involves testing all models using the test set (15%) to obtain accuracy, precision, recall, and F1-score values. These metrics are calculated using the equations provided in (1)-(4) [13], [23].

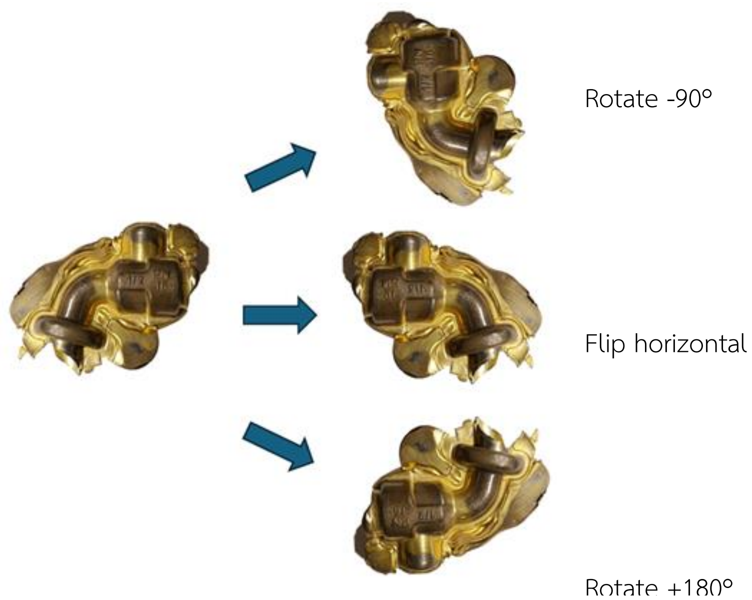

Fig. 2. Generating of three augmented images from an original image using rotation and flipping, for example.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + True\ Negatives + False\ Positives + False\ Negatives} \quad (1)$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (2)$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (3)$$

$$F1 - score = \frac{True\ Positives}{2(True\ Positives) + False\ Positives + False\ Negatives} \quad (4)$$

After completing the final steps, the outcomes of both model validation and testing, encompassing accuracy, precision, recall, and F1 -score, are collated for presentation in the following section.

RESULTS

After conducting the processes as presented in Fig. 2, every model was trained using two classes of images of WIP - water taps. Then, the accuracy, precision, recall, and F1-score of each model under each condition were evaluated before presenting all results associated with values of accuracy, precision, recall, and F1-score in Table II.

As presented in Table II, it is evident that ResNet50 and EfficientNetB0 exhibit the highest accuracy, precision, recall, and F1-score values of 100% in both the validation and test sets. This indicates that ResNet50 and EfficientNetB0 emerge as the top-performing models compared to others in this study, based on the evaluation results. Following closely, DenseNet121 demonstrates accuracy, precision, recall, and F1-score values of 100% when tested with the validation set. However, when evaluated with the test set, it registers values of 99.003%, 99.002%, 99.006%, and 99.003%, respectively. MobileNet becomes the next position, with accuracy, precision, recall, and F1-score values of 99.667%, 98.936%, 99.000%, and 99.667%, respectively, in the validation set. Nonetheless, when assessed with the test set, it records values of 99.668%, 99.673%, 99.664%, and 99.668%, respectively. Occupying the last two positions are Xception, and InceptionV3, respectively. Further details are provided in Table II.

TABLE II. THE RESULTS

Model	Accuracy (%)		Precision (%)		Recall (%)		F1-score (%)	
	Validation set	Test set	Validation set	Test set	Validation set	Test set	Validation set	Test set
ResNet50	**100.000**	**100.000**	**100.000**	**100.000**	**100.000**	**100.000**	**100.000**	**100.000**
MobileNet	99.667	99.668	98.936	99.673	99.000	99.664	99.667	99.668
Xception	96.333	97.010	95.833	97.015	95.913	97.006	96.333	97.009

Model	Accuracy (%)		Precision (%)		Recall (%)		F1-score (%)	
	Validation set	Test set	Validation set	Test set	Validation set	Test set	Validation set	Test set
InceptionV3	95.833	95.349	95.826	95.370	95.826	95.362	95.826	95.349
EfficientNetB0	**100.000**	**100.000**	**100.000**	**100.000**	**100.000**	**100.000**	**100.000**	**100.000**
DenseNet121	**100.000**	99.003	**100.000**	99.002	**100.000**	99.006	**100.000**	99.003

DISCUSSION

It is evident that the accuracy, precision, recall, and F1-score results from four out of six models, evaluated with the augmented dataset, exceed 99.00% in both the validation and test sets. Additionally, it can be observed that each accuracy result aligns consistently with the respective F1-score result provided by each model. Moreover, the highest accuracy of 100% achieved by ResNet50 and EfficientNetB0 may be attributed to their performance or efficiency, while factors such as the fixed pattern and the limited number of classes—only two classes—may also significantly influence these outcomes. Furthermore, when compared to previous works, the result from EfficientNet-B0 is consistent with the results presented in [25] that EfficientNet-B7, which is one of its family, shows high accuracy (95.20%) compared to other models, except the proposed GabageNet-family models. Besides, the high accuracy result from ResNet50 in this study is consistent with the high accuracy results of 99.10% and 99.07% from ResNet34 and ResNet152 respectively, as presented in [26-27].

Thus, ResNet50 and EfficientNetB0 can be considered for the development of the new automatic station for checking the WIP before delivery to the next station. However, advancing beyond reference [2], this study was conducted with additional transfer models. Also, the size of each model has been retrieved and presented in Table III. One can see that the size of the EfficientNetB0 model, which has an accuracy and related results of 100%, is only 15.48 MB, smaller than the size of the ResNet50 model (90.03 MB). Therefore, EfficientNetB0 should be considered the best option in this study for developing the new automatic station using computer vision technology for checking the WIP before delivery to the next station by rejecting unwanted parts in the future. However, from Table III, one can observe that MobileNet is the smallest model size, while it has an accuracy and related results of more than 99%. Its accuracy result is also consistent with the result of 99.84 from MobileNetV3 presented in [26]. Therefore, MobileNet might be considered as an alternative option for the new automatic station in the future.

TABLE III. THE MODEL SIZES

Model	Size (MB)	Remark
ResNet50	90.03	The largest
MobileNet	12.34	The smallest
Xception	79.63	
InceptionV3	83.22	
EfficientNetB0	15.48	
DenseNet121	26.87	

CONCLUSION AND FUTURE WORKS

After conducting this study on copper-based alloy water tap images using deep learning, it was found that ResNet50 and EfficientNetB0 provided the highest accuracy (100%), while MobileNet ranked second with an accuracy of approximately 99.67% when evaluated with the test set. This test set was part of an augmented dataset consisting of 1,000 images per class, created from an original set of around 300 images per class. However, considering the model sizes, EfficientNetB0 with only 15.48 MB, is smaller than ResNet50, which is approximately 90 MB. Therefore, EfficientNetB0 emerges as the optimal choice for developing an automatic detection and rejection system in the production line of a water tap manufacturer in the future.

However, this study utilized geometric-based augmentation techniques (e.g., rotation and flipping) exclusively. Future work should incorporate other augmentation techniques (e.g., noise addition) to further diversify the dataset. This expansion can enhance the variety of images for dataset enlargement. Additionally, this study was confined to only two classes of water taps. Subsequent research should investigate additional classes of water taps and integrate more augmentation techniques. Furthermore, the concepts introduced in this study could be extrapolated to other products across diverse industries.

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