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Deep Learning Based Visual Automated Sorting System for Remanufacturing

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***Abstract*—Remanufacturing is a crucial component of the circular economy concept which emphasises sustainable consumption habits. This study proposes a novel automated sorting system for remanufacturing which is based on deep convolutional neural networks(CNN). To demonstrate its applicability, the proposed deep learning (DL) system was used to distinguish among dry, wet, oily and defected surfaces. The test was conducted on four locally sourced 3" x 6 " plates. Sample image data were captured using a USB webcam. The network training was done with 75% of the data while the balance data were used for testing. In this preliminary study, the DCNN classified the features with up to 99.74% accuracy on validation data and above 96% accuracy on live video feed; demonstrating that it can accurately sort components. This study is the first to propose a low-cost sorting system for remanufacturing based on the deep CNN and logic gates. The results show that the method is an accurate, reliable, cost-effective and fast technique that can potentially outperform existing sorting systems in the remanufacturing industry.**

Keywords: remanufacturing, sorting in remanufacturing, sorting systems, deep learning for sorting

I. Introduction

Remanufacturing is a technique of returning used products to at least original equipment manufacturer(OEM) original performance specification from the customers' perspective, with the resultant product matching a warranty that is at least equal to that of a newly manufactured equivalent [1]. Generically, the restoration is an industrial process which involves accessing used products with substantial value, sorting the recovered, similar or damaged products, cleaning and disassembling, and inspection, to determine which ones are to be replaced or reworked, and afterwards, reassembled. The resultant product is tested to ascertain that it functions as good as new ones.

The remanufacturing process is usually described as complicated and stochastic by nature, mainly due to the unpredictable conditions and quantity of returned products [2]. In addition, the Remanufacturing operations are mostly manual [3], and involve numerous uncertainties, primarily due to the dissimilarity of used products returned for remanufacturing. This variation is usually due to different conditions of use. It limits the ability of conventional sorting systems based on geometry, to be applied in automating the remanufacturing process without modifications.

This study focuses on developing a deep CNN-based sorting system for remanufacturing. Unlike similar studies that perform sorting as a mere recognition of an entire object, the proposed system aims to use the deep CNN(DCNN) to detect features such as surface conditions, thereby demonstrating its ability to recognise faults on components. The advantage of this method is the simplicity and capability to recognise features without being explicitly programmed.

The remaining parts of this paper have Section 2 detailing the related works, Section 3 discusses the CNN, Section 4 outlines the design of the proposed DCNN, Section 5 highlights the implementation, Section 6 presents the experimental results obtained. Finally, Section 7 provides the conclusion.

II. Related Works

Image recognition is among the most currently researched problems in machine learning and computer vision fields. It uses the keypoint based approach, which is a gradient-based approach where the local gradient information of an image is used to obtain interest points within an image also known as keypoints. Thus changes in pixel characteristic in definite directions of x and y are used in their local neighbourhood. It has been used for developing sorting systems. A typical application, as the Oriented FAST and rotated BRIEF (ORB) [4] algorithm.

Furthermore, the rule-based decision approach for automated identification utilises a recognition logic which consists of barcodes, identification numbers and other object-inherent features like weight, visual appearance, dimensions and volumetric representations [5]. Conversely, radio frequency identification (RFID), which is another technique used in the design of sorting systems for remanufacturing. This approach uses an RFID tag, attached or embedded to a product to store, process and transfer relevant product data to the users or company in an effective way through some communication systems [6]. It offers some benefits compared to the bar code system used in the rule-based approach as it gathers and processes data with accuracy and speed. It also performs well in most harsh environmental conditions. However, a major highlighted limitation is the inaccuracy arising from missing data and reading errors which makes them unsuitable in some applications [7].

Nevertheless, the learning-based approach uses the machine learning approach to recognise end-of-life products from video streams, thereby managing EoL waste streams [8]. This approach identifies the incoming EoL product automatically and predicts the appropriate EoL process suitable for that product. It uses CNN and provides the advantage that it does not perform manual feature detection and extraction like the key-point based approach, does not require the bar-codes like the rule-based based approach, and does not suffer from missing data as highlighted in the RFID approach. The current implementation of CNN in remanufacturing is limited to image classification based on key colour extraction [8] in which only three distinct objects were used for the network training, thereby limiting its ability to recognise the same object when different features are embedded on it.

III. Convolutional Neural Networks

The CNN is a deep multi-layer architecture used to learn and categorize patterns that are structured in layers. The architecture comprises of input layers, hidden layers which are sets of independent neurons, having sub-layers including the convolutional layers, the pooling layers, the activation functions, loss layers and the fully-connected layers, and the output layers [9], with the convolutional layer, being the main building block. It modifies the input data with the help of a patch of neurons locally connected from the preceding layers using the dot product. It also uses the convolution operation, inspired by the need to share parameters, sparse interactions and equivariant representations [10]. The convolution operation is represented by the equation:

$$h(t) = (x * k)(t) \tag{1}$$

Where $*$ represents the convolution operation, and h,x,t,k represent the output, input, time, and kernel of the neural network parameters respectively. The output is often referred to as a feature map and typical CNN architectures include AlexNet [11], ResNet [12], SeNet [13], among others.

A. AlexNet Architecture

The AlexNet is a CNN, trained on over one million images from the database of images known as ImageNet. The architecture is an eight-layer neural network with five convolutional layers and three fully connected layers. It uses images of size [227,227,3], with dropout applied before the first and second fully connected layers, as well as max pooling, ReLU and softmax functions batch normalisation and a loss optimisation [11]. The AlexNet is adopted in the design of this automated sorting system.

IV. Automated Sorting in Remanufacturing

The automated sorted system for remanufacturing is a DL based model for sorting in remanufacturing. The application of the DCNN in automated sorting is based on its capability to recognise objects features from video streams. The system is modelled as a classification problem where several metrics are used to ascertain model performance, including precision, recall and accuracy. The accuracy defines the ratio of the number of incorrectly classified samples to the total number of classified samples. It is often defined in terms of precision and recall for binary classification.

For multi-class models, the accuracy is defined in terms of the total number of predictions that the model predicted correctly through the combination the precision and recall [14]. Accuracy (Acc) is obtained using the relationship.

$$Acc = \frac{totalcorrectpredictions}{totalpredictions} = \frac{TP + TN}{TP + FP + TN + FN} \tag{2}$$

Where TP = true positive, FP = false positive, TN = true negative and FN = false negative. The accuracy metric was chosen because the dataset has a balanced distribution that aids the performance of multi-class based system. This system consists of a USB camera, a computer with a graphics processing unit (GPU) and a computational model, used to analyse the camera video. The model is a modified Matlab based pre-trained AlexNet where the output layer and other parameters were optimised to suit the data. The model recognises the objects from the visual system and sorts them into categories using the actuation system. This actuation system comprises of simple logic gates although programmable controllers like the programmable logic controllers could be modified to achieve the setup. The process block diagram of the proposed setup is shown in Figure 1, depicting the key stages of the sorting system pipeline.

Fig. 1. *System block diagram*

A. Training the Network

To train the modified AlexNet model, the stochastic gradient descent with momentum optimiser was used, with a mini-batch size of 32, dropout of 50%, the categorical cross-entropy loss function, ReLU and softmax activation functions, of which [15] provides detailed discussions on the different AFs. The idea is to reduce the model loss to zero; however, this is not practically possible in most cases. The Matlab network training progress plot was used to monitor the training.

V. Proposed Sorting System Setup

The proposed sorting system was designed to have a minimum of four object categories. The sorting of each class is performed using three-sided actuators placed in series. The novelty of this approach is that we considered the same objects having different surface conditions as our categories while most of the existing vision-based systems considered one object per class. This makes our approach suitable for sorting based on the surface characteristics of the object. The significant advantage of this system is that it can be incorporated easily into other parts of remanufacturing systems with little modification. The implementation includes a conveyor system to move cores through the sorting process. A live streaming video camera, positioned to have a clear view of the object records the object as the components move. The connected

PC quickly performs the necessary processing, to recognise the fault on the object. The detected category of the object actuates the system using a logic system, on the arrival of the object, thereby sorting them.

The distance between the camera and the objects was fixed to 30” and arranged for real industrial application. As lighting was a contributing factor to this task, we adjusted the gap between the camera and the surface for better inspection, especially to accurately visualise the contaminated surfaces.

VI. Evaluation of the Designed System

The evaluation of this experiment was conducted in two stages, including testing on the validation set and live video. The accuracy metric was used to measure model performance. The model accuracy is reported in two stages which include the training accuracy and the validation accuracy. An impressive training accuracy of 100% was obtained, while a validation accuracy of 99.74% on the samples. These results show that the model performed remarkably well on sorting these objects based on their surface conditions. The visualisation of the model performance is shown with the confusion matrix in Figure 2, which describes the model performance in table form for supervised learning problems.

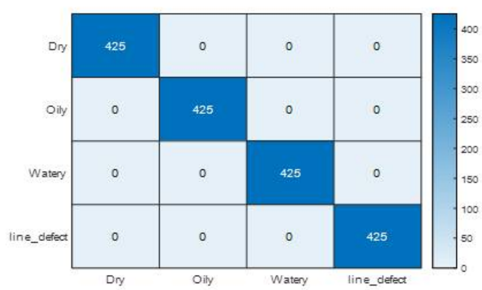

Fig. 2. *Heatmap of the results of the developed DCNN sorting system.*

From the confusion matrix, we can observe that across all categories, the model produced correct classification results in all the four classes. Furthermore, the second evaluation stage described as the online setting stage involved using the USB webcam camera clamped on the workbench, with the objects on the floor of the workshop, at approximate 30” distance from the camera. The pre-trained network was loaded alongside the camera preview. For the online sorting setting, the slight reduction in accuracy was obtained results for some samples categories, as we take the components away from the camera. This manifests in the confidence levels observed in the results of the system prediction lying between 96% to 100% confidence level across all the categories investigated. The model shows a slightly lower prediction accuracy in the online setting compared to the validation data, but suggests that the system was able to sort the respective categories to very high accuracy. These limitations can be improved by data augmentation and by permanently fixing the camera location before data capture.

VII. Conclusion

This work demonstrates the possibility of performing surface condition-based visual automated sorting for remanufacturing. The system was able to sort parts from live video feed using DCNN. This proof of concept DCNN vision-based sorting system can be used to perform industrial sorting applications when deployed. Finally, the benefits of this sorting approach are that it can perform component sorting, even on contaminated surfaces. Among the benefits of the proposed sorting system, is the cheap cost of deploying the proposed method, especially as we developed the system using a £4 worth camera as a vision sensor. A more powerful camera can achieve even a higher-grade sorting system but would increase the cost of deploying this system for sorting applications in remanufacturing. The limitation of the current study is that it was performed on experimental samples. Potential future work is to expand the technique developed to an industrial scale. Such an application would enhance remanufacturing automation.

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