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Research on Damage Defect Detection Based on Computer Vision

Chhavi Rajput
PGCP from Indian Institute of Technology,
Guwahati in Artificial and Deep Learning

Abstract:- When an customer places an order online, they expect a fast and accurate delivery. Customer demand for a seamless experience from placing an order to receiving an undamaged order in the hands. To provide this seamless experience to our customers, large level of industrialization is happening on the backend from picking each product, scanning the barcode and putting the order on the conveyor belt after packaging and shipping the order at the right address. However, automation comes with certain risks of mis-sortation of packages, damage defects during packaging the product, barcode sticker alignment and the received product can be hampered due to liquid spillage, open damage box, uncovered tape and other factors.

Therefore, this research is an effort to identify the damages and defective products before delivering the order. With the help of computer vision technology, cameras are placed on the top of each conveyor belt and camera will share the images at every 3-5 seconds and advance algorithm will be used to identify the defects or damage packages. This paper will cover the computer vision algorithm along with image processing normalization techniques to identifying the damages due to human interaction and leading late deliveries and poor customer experience.

Keywords:- *Image Processing, Computer Vision, Defect Detection.*

I. INTRODUCTION

Operational development is a driving force of automation and improving customer experience. Computer vision based automated damage defect detection systems can help ecommerce enterprises achieve this goal by improving customer experience, product quality and market competitiveness by reducing the defect. At the same time, this process will reduce the cost of manual inspection and improve production. This damage defect detection computer vision algorithm has the capability to identify the damages by looking at the image coming from cameras and sensors. Our world is moving fast towards computer vision and industries need advance computer vision based systems to improve productivity and reduce packaging defects and enhance capabilities of future industrial development [1].

This paper will explore the computer vision, image processing methods to identify the damages and defective products, revealing its potential from implementation point of view and prospects in ecommerce industry. Firstly, it will review the image processing, computer vision and deep learning aspects that are part of this research of identification of damage defect detection. In addition to introducing the automated damage defect detection system based on computer vision, this paper also aims to stimulate thinking about the future application of computer technology. In this fast moving era, computer vision is also helping the world to drive autonomous car driving by identifying and segment the each object in the frame and take the decision accordingly[2]. By merging industrialisation with advance technology, it breaks the traditional methodology and provides people seamless experience of services and intelligent way of thinking.

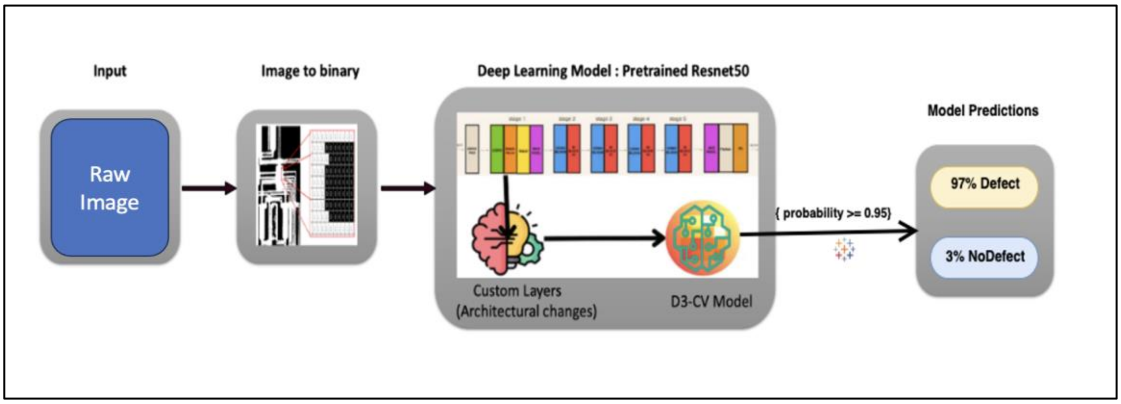

Fig. 1 High Level Diagram of Damage Defect Detection Computer Vision Model

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II. MODELS AND ALGORITHMS FOR DAMAGE DEFECT DETECTION BASED ON COMPUTER VISION

In any industry, the biggest challenge is to transform business problem into machine learning and AI problem statement. There are several examples in real time where automation and ML can be applied. Framing an ML problem is the most creative and approachable way to solve any machine learning problem. In this paper, our main focus is to ***identify the defects and no-defects***, to improve the customer experience by not delivering the damaged product and identify the damage packages at first place. This will be an image classification problem, where binary classifier will predict the **defect** and **no-defect** categories with probability or confidence score. Image processing and image classification is a core filed of computer vision and deep learning. It gives an advance opportunity of rapid development towards deep learning and machine learning. Advance image processing algorithm helps to read the useful features from the images and categorize them into pre-defined classes. ImageNet[3] is a large scale data set of images related to each category, this help researchers to use pre-trained models directly and researchers can start their work with small dataset. ImageNet contains 14 million images with 20000+ categories. Image classification[4] involves categorizing or labelling images or specific areas within them. This process offers a comprehensive understanding of the image's content and can be carried out using either traditional methods or deep learning techniques. Popular deep learning CNN architectures include Alexnet, ResNet20, VGGNet16, and ResNet50. In this paper, experimentation based on transfer learning and ResNet50 pre-trained models will be presented. Since it has lots of advantages compare to other deep neural network architectures, in term of training time, learning pattern etc. Transfer learning is a reliable source for experimenting with small dataset of images and transfer learning models are already trained on large dataset to give the desire output by tuning hyperparameters and architectural changes.

Table 1 Experimentation on Different Pre-Trained Models

Model Name	Model Training Results	Model Metrics
AlexNet	Epoch 30/30 [==============================] - 75s 709ms/step - loss: 0.5612 - accuracy: 0.7065 - val_accuracy: 0.8133	Specificity: 75% Sensitivity: 87% ROC-AUC: 0.81 Accuracy: 81% Balanced Accuracy: 81% Matthews Correlation Coefficient: 0.63
VGG16	18/50 [==============================] - 95s 902ms/step - loss: 0.7819 - accuracy: 0.9440 - val_accuracy: 0.8504	Specificity: 0.86% Sensitivity: 0.85% ROC-AUC: 0.86 Accuracy: 0.86% Balanced Accuracy: 86% Matthew Correlation Coefficient: 0.72
ResNet50 with Image Augmentation	With 3 Dense and 2 Drop out layers106/106 [==============================] - 67s 634ms/step - loss: 0.0378 - accuracy: 0.9882 val_accuracy: 0.8628	Specificity: 87% Sensitivity: 89% ROC-AUC: 0.88 Accuracy: 88% Balanced Accuracy: 88% Matthew Correlation Coefficient: 0.77

III. IMAGE AUGMENTATION

Training a model on large datasets presents a significant real-time challenge in deep learning. Deep learning and computer vision tasks have achieved remarkable results thanks to the use of convolutional neural networks (CNNs). However, diverse dataset for training has become a necessary part for computer vision models. Image Augmentation [5] is a process to diversify the data based on the existing dataset. Computer vision models rely on a large amount of data for training, but for certain types of images there aren't enough examples to provide a robust representation of the data. For example, if we are training a model to identify images of defects in products, there are many images of Empty and No Defect cases but relatively few images of different types of defects. Let's say the split is 95% No Defects, and 5% Defects. This means that the training process may lead to an inefficient representation of the data, resulting in models that are highly specific and less robust. In our case, the models will be highly accurate for No Defects, but less accurate for all the different types of defects. In this use case, image augmentation would be optimal approach to handle imbalance dataset. Image augmentation involves creating additional examples from the original dataset, but with slight alterations such as flipping images vertically or creating mirrored images. This will increase the number of images in the underrepresented classes and yield a more balanced dataset. Image augmentation helps this experiment to augment the images by rotating the image on different angles, along with cropping and blurring technique. Image augmentation helps this model to increase 12% specificity and 2% sensitivity from AlexNet to ResNet50 with image augmentation. Model is capable to identify the 82% (441/536) of missorts defect and 61% (464/750) of the overall defects with 95% high confidence and 91% precision rate.

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IV. CONCLUSION

This paper introduces a computer vision model for damage and defect detection, designed to enhance the quality and packaging processes in e-commerce fulfilment centres by identifying damaged products. Leveraging three key technologies — image augmentation and pre-processing, computer vision, and defect recognition and classification — the model operates with high efficiency and accuracy to detect mis-sorted items, label defects, and other damages, with the ultimate goal of achieving real-time monitoring and automatic detection on production lines. This approach significantly boosts detection efficiency and accuracy, while minimizing human intervention and the risk of misjudgement. At the core of the system are computer vision techniques and deep learning algorithms, which play a crucial role in enabling precise defect detection. Although many deep learning models currently offer promising results, providing the required detection accuracy and speed for industrial production lines, challenges remain, particularly around privacy and security concerns. However, it is anticipated that these issues will be addressed in the future. With the continued development of advanced models, the system's detection accuracy, real-time performance, and robustness will improve, broadening its applications and prospects for future growth.

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