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Casting Product Image Data for Quality Inspection with Xception and Data Augmentation

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Abstract: ***Casting defects encompass a broad spectrum of imperfections, such as blow holes, pinholes, burrs, shrinkage defects, and various metallurgical anomalies. Detecting these defects manually requires a trained eye, and even the most diligent inspectors can inadvertently overlook subtle irregularities. To address these challenges, there is a growing movement toward automation in quality control. Deep learning models, including the Xception model, are being harnessed to create a robust classification system. Such models have the capacity to analyze thousands of product images with precision, identifying defects that may elude human inspectors. Furthermore, data augmentation techniques are applied to enhance the dataset, allowing the model to generalize more effectively and improve its defect recognition capabilities.***

Keywords: Casting product image; Xception Model; Data Augmentation.

1. INTRODUCTION

Quality inspection plays a pivotal role in the casting manufacturing industry, ensuring the production of flawless products. Casting defects pose a significant risk, potentially leading to substantial financial losses. Manual inspection processes, however, prove time-consuming and prone to errors. Casting defects encompass various imperfections, ranging from blow holes to metallurgical anomalies [1]. Detecting these defects manually requires a trained eye, and even diligent inspectors can overlook subtle irregularities.

Numerous groundbreaking studies have paved the way for casting product image analysis. Researchers have delved into the application of Computer-Aided Engineering and Convolutional Neural Networks (CNN) to elevate the quality inspection process in casting manufacturing. Some researchers [2][3] exemplify the expanding utilization of deep learning techniques within this domain, reflecting a growing trend in enhancing quality control in casting manufacturing. Nevertheless, even with these notable strides, challenges persist in the field. One paramount issue involves effectively managing uncertainty in the defect detection process [4]. Although these studies make substantial contributions to bolstering accuracy in quality control, there remains untapped potential for deep learning methods to grapple with intricate data complexities [5]. Addressing these challenges is essential for further advancements in quality control within the casting industry.

To address these limitations, our research proposes a robust approach that leverages the Xception model [6] and employs data augmentation [7][8]. The Xception model, known for its excellence in image classification, offers enhanced capabilities in recognizing intricate patterns in casting images. Data augmentation further enriches our dataset, ensuring the model's ability to generalize effectively and improve defect recognition. This innovative combination promises to significantly advance the state of automated quality control in the casting industry, improving both precision and recall.

2. RELATED WORK

A number of initial publications established the groundwork for the casting product images. "Casting product image data for quality inspection" is a valuable resource in the field of quality control for casting products. This dataset, categorized into "Defective" and "Ok" classes, is instrumental for the development of automated systems that enhance the efficiency and precision of quality control processes in the casting industry. Seokju et al. [2] discusses the use of Computer-Aided Engineering (CAE) and Convolutional Neural Networks (CNN) for enhancing the quality inspection process in casting manufacturing. Nguyen et al. [3] presents a method for inspecting defective casting products using Convolutional Neural Networks (CNN). This approach aims to enhance the efficiency of quality control in casting, reducing the incidence of substandard products in the market. The paper delves into the application of CNN models and their integration into the quality inspection process. It serves as a valuable reference for the casting industry.

Advancements in casting product images. research have encompassed a wide spectrum of areas, including addressing incorporating more and more deep learning methodologies. Habibpour et al. [4] presents a deep learning framework tailored for defect detection in casting products, addressing uncertainty within the process. It is a valuable resource for enhancing accuracy in quality control and inspection processes in the casting industry. Gupta et al. [5] proposes a deep learning model for the analysis of defects in industrial casting images. The model aims to automate defect detection, enhancing quality control processes in the manufacturing industry.

3. ALGORITHM AND MODEL

3.1 Xception model

The Xception model, an advancement of the conventional convolutional neural network (CNN), is a pioneering architecture in deep learning for image classification. As shown in Figure 1, depthwise separable convolutions enhance the efficiency and performance of image recognition. At the core of Xception lies depthwise separable convolution, which divides the standard convolution into two steps: depthwise and pointwise convolutions.

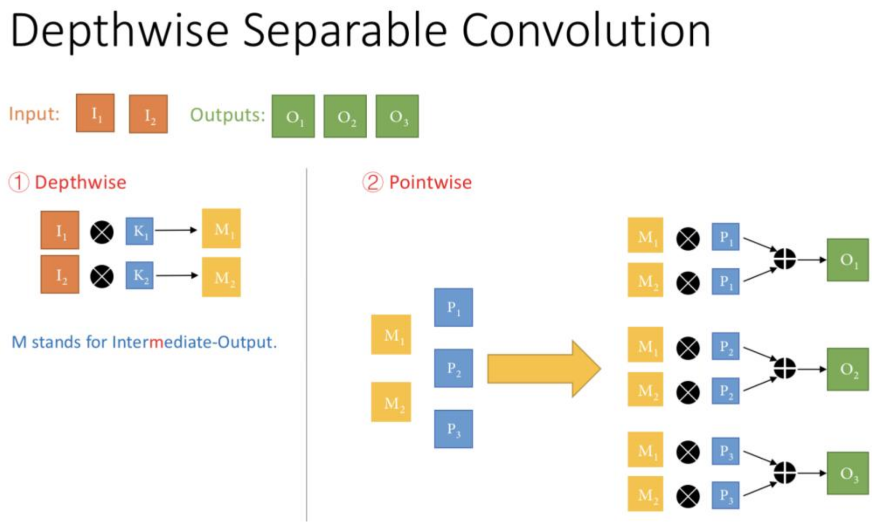

Figure 1: Depthwise separable convolution

This approach reduces parameters and computational complexity, making it ideal for large image datasets. Mathematically, the depthwise separable convolution is represented as:

Depthwise Convolution:

$$y(x,k) = w_k * x(k) \tag{1}$$

Pointwise Convolution:

$$z(x,k) = w_k' \cdot y(x,k) \tag{2}$$

Here, $y(x, k)$ is the result of depthwise convolution for the k-th channel, $z(x, k)$ is the outcome of pointwise convolution, w_k and w_k' are the convolutional filter and weight for the k-th channel, and x is the input data.

Xception excels at pattern generalization, especially when coupled with data augmentation. For binary classification, we use binary cross-entropy [9] as the loss function:

$$L(y,p) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \cdot \log(p_i) + (1-y_i) \cdot \log(1-p_i)] \quad (3)$$

Here, $L(y,p)$ is the binary cross-entropy loss, N is the number of samples, y_i is the true binary label (0 for "Ok" and 1 for "Defective") for the i-th sample, and p_i is the predicted probability that the i-th sample belongs to the "Defective" class.

3.2 Data Augmentation in the Model

Data augmentation is a crucial component of our approach to enhance defect detection using the Xception model. In the context of image classification and quality control for casting products, data augmentation serves several essential purposes:

1. **Diversity Enhancement:** Casting product images can vary significantly in terms of orientation, lighting conditions, and background clutter. Data augmentation techniques such as rotation, scaling, and flipping create diverse versions of the original images, exposing the model to a wider range of scenarios. This diversification is vital as it ensures that the model can accurately identify defects in casting products under various real-world conditions.

2. **Generalization:** The Xception model's remarkable ability to generalize patterns can be further amplified with data augmentation. By presenting the model with augmented data, we allow it to learn from a broader set of features and patterns, making it more robust in recognizing defects. This capacity for generalization is particularly important when dealing with novel casting defects that may not be explicitly represented in the original dataset.

3. **Improved Model Performance:** The combination of data augmentation and the Xception model empowers our system to achieve higher accuracy in identifying casting defects. By exposing the model to a wider spectrum of data, we enhance its ability to make precise classifications, reducing the risk of false negatives or positives in the quality control process.

In our research, we utilize the Xception model alongside data augmentation and the Adam optimization [10] algorithm for training. The Adam optimizer adapts learning rates for each parameter during training, enhancing the convergence and training speed [11]. This combination promises to improve defect detection accuracy and overall efficiency in the quality control process.

4. EXPERIMENTS

4.1 Datasets

This dataset encompasses 7348 grayscale images of submersible pump impellers, with a primary focus on the identification of casting defects. The dataset's core objective is to revolutionize quality control processes within the casting industry by replacing labor-intensive and error-prone manual inspections with automated deep learning models. Images are divided into two fundamental categories: "Defective" and "Ok." The dataset includes images of two sizes, 300x300 and 512x512 pixels, and comes equipped with pre-applied augmentations. Captured under stable lighting conditions, it is thoughtfully split into training and testing sets, containing 3758 "Defective" and 2875 "Ok" images in the training set, and 453 "Defective" and 262 "Ok" images in the test set, making it a crucial resource for the development of automated casting defect detection models.

4.2 Evalution metrics

Precision, Recall, and F1-score are the measures used in the named entity recognition. P (Positive) represents positive samples in all the samples. N (Negative) represents negative samples in all the samples. TP (True Positives) is the number of positive samples predicted as positive. FN (False Negatives) is the number of positive samples predicted as negative. FP (False Positives) is the number of negative samples predicted as positive. TN (True Negatives) is the number of negative samples predicted as negative. Precision is the proportion of true positive samples in all the samples that are predicted to be positive, which is defined as:

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

Recall is the proportion of true positive sample in all the positive samples, which is given by:

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

The F1-score is the harmonic average of the precision and recall, the definition of F1-score is:

$$F1 = \frac{2*Precison*Recall}{Precision+Recall} \tag{6}$$

4.3 Results

The evaluation of various deep learning models for casting product defect detection demonstrates their effectiveness in enhancing the quality control process. The table below presents the precision, recall, and F1-score metrics for different models, each catering to specific requirements.

Table 1: Model Results

Model	*Precision*	*Recall*	*F1-Score*
ResNet50	0.8456	0.7818	0.7850
CNN	0.9802	0.9790	0.9791
InceptionV3	0.9848	0.9846	0.9846
Xception	0.9852	0.9846	0.9847
Xception Aug	0.9916	0.9916	0.9916

ResNet [12] provides a good balance between precision and recall, achieving satisfactory F1-Score. The CNN [13] model demonstrates an exceptional balance between precision and recall, leading to an outstanding F1-Score. InceptionV3 [14] and Xception deliver consistently high precision, recall, and F1-Score, making them robust choices for defect detection. Notably, the Xception model, when combined with data augmentation known as Xception Aug, stands out as the top performer, showcasing the highest precision, recall, and F1-Score, making it the preferred choice for accurate quality control in the casting industry. These results highlight the promising potential of deep learning models, especially when combined with data augmentation, in automating quality control and significantly improving the accuracy of defect detection processes within the casting manufacturing domain.

5. CONCLUSION

During this era of swift advancements in artificial intelligence across multiple domains, numerous fields are witnessing a significant increase in the adoption of AI technologies, showcasing the significant impact and potential of AI-driven solutions. Our study delves into the utilization of deep learning models, particularly the Xception model with data augmentation, represents a transformative advancement in the field of casting product quality inspection. Casting defects, a long-standing challenge in the industry, can be effectively addressed through automated defect detection. Our approach, combining state-of-the-art models with diverse data augmentation techniques, not only enhances defect recognition accuracy but also ensures robust performance under varying real-world conditions. The results clearly demonstrate the potential of this approach, with the "Xception aug" model achieving exceptional precision, recall, and F1-Score. This research heralds a new era in casting quality control, promising heightened efficiency, reduced financial losses, and enhanced product quality.

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