Automated Defects Detection in Manufacturing using Convolutional Neural Networks

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***Abstract*—Defects detection in manufacturing is an essential component of industrial production quality control. The combination of image processing and convolutional neural networks (CNNs) has developed as a potent solution to deal with this issue. This paper examines the creation of a reliable system for defect detection in manufacturing, leveraging the power of image processing and CNNs. This novel method analyzes visual data taken during the manufacturing process to find and categorize defects from small imperfections to serious flaws. This system makes use of image preprocessing methods to improve image quality and extract required features. Using the labelled data, convolutional neural networks are trained to accurately diagnose the defects. This approach gives several benefits that include automation, monitoring in real-time, and consistent outcomes which reduce human faults and production downtime. Finally, the combination of image processing and CNNs for defect detection in manufacturing assures to improve product quality with efficiency by curtailing production value and waste.**

Keywords*— *Machine Learning, Automation, Defect Detection in Manufacturing, Image Processing, Convolutional Neural Networks (CNNs)

I. INTRODUCTION

The manufacturing industry has undergone a remarkable transformation in recent years, with an increasing reliance on automation and technology to ensure product quality and efficiency. One of the critical aspects of this evolution is defect detection, which plays a pivotal role in ensuring the integrity of the products being produced. Manufacturing Defect Detection using Image Processing and Machine Learning represents a cutting-edge approach to addressing this challenge.

In the context of modern manufacturing, where high precision and minimal error rates are paramount, the combination of image processing and machine learning has emerged as a powerful tool. This innovative approach involves the utilization of advanced image capture systems, such as cameras and sensors, to acquire detailed visual data of the products as they move through the production line. This data is then processed and analysed using machine learning algorithms, which can identify even the most subtle defects that might be imperceptible to the human eye.

The integration of image processing and machine learning for defect detection offers several advantages. It not only enhances the speed and accuracy of defect identification but also reduces the reliance on manual inspections, leading to significant cost savings. Furthermore, it enables early detection of defects, preventing substandard products from reaching the market and ensuring that only high-quality items are delivered to customers.

This approach has applications in various manufacturing sectors, including automotive, electronics, pharmaceuticals, and consumer goods, to name just a few. With the continual advancement of image processing techniques and machine learning algorithms, Manufacturing Defect Detection using Image Processing and Machine Learning promises to be an indispensable tool for improving product quality and reliability in the manufacturing industry. The rest of the paper is organized as follows: section II gives related work for defects detection in manufacturing Section III gives in detail of Convolutional Neural Network. In section IV, proposed methods with all steps discussed. Section V discusses the designing and implementation. Section VI the results. Finally, Section VII concludes the work and Section VIII gives future direction.

II. LITERATURE REVIEW

Caggiano et al [1] developed a machine learning approach for on-line fault recognition via automatic image processing to timely identify material defects due to process non-conformities in Selective Laser Melting (SLM) of metal powders. In-process images acquired during the layer-by-layer SLM processing are analysed via a bi-stream Deep Convolutional Neural Network-based model, and the recognition of SLM defective condition-related pattern is achieved by automated image feature learning and feature fusion. Experimental evaluations confirmed the effectiveness of the machine learning method for on-line detection of defects due to process non- conformities, providing the basis for adaptive SLM process control and part quality assurance.

Ren Zhonghe, et al [2] used Machine vision which significantly improves the efficiency, quality, and reliability of defect detection. In visual inspection, excellent optical illumination platforms and suitable image acquisition hardware are the prerequisites for obtaining high- quality images. Image processing and analysis are key technologies in obtaining defect information, while deep learning is significantly impacting the field of image analysis. In this study, a brief history and the state of the art in optical illumination, image acquisition, image processing, and image analysis in the field of visual inspection are systematically discussed. The latest developments in industrial defect detection based on machine vision are introduced. In the further development of the field of visual inspection, the application of deep learning will play an increasingly important role. Thus, a detailed description of the application of deep learning in defect classification, localization and segmentation follows the discussion of traditional defect detection algorithms. Finally, future prospects for the development of visual inspection technology are explored.

Li et al [3] proposed a scheme based on Machine Learning (ML) models to detect geometric defects of additively manufactured objects. The ML models are trained with synthetic 3D point clouds with defects and then applied to detect defects in actual production. Using synthetic 3D point clouds rather than experimental data could save a huge amount of training time and costs associated with many prints for each design. Besides distance differences of individual points between source and target point clouds, this scheme uses a new concept called “patch” to capture macro-level information about nearby points for ML training and implementation. Numerical comparisons of prediction results on experimental data with different shapes showed that the proposed scheme outperformed the existing Z-difference method in the literature. Five ML methods (Bagging of Trees, Gradient Boosting, Random Forest, K-nearest Neighbors and Linear Supported Vector Machine) were compared under various conditions, such as different point cloud densities and defect sizes. Bagging and Random Forest were found the two best models regarding predictability; and the right patch size was found to be at 20. The proposed ML-based scheme is applicable to in-situ defect detection during additive manufacturing with the aid of a proper 3D data acquisition system.

Yang et al [4] adopted actual intelligent production requirements and proposed a tiny part defect detection method to obtain a stable and accurate real-time tiny part defect detection system and solve the problems of manually setting conveyor speed and industrial camera parameters in defect detection for factory products. First, they considered the important influences of the properties of tiny parts and the environmental parameters of a defect detection system on its stability. Second, they established a correlation model between the detection capability coefficient of the part system and the moving speed of the conveyor. Third, they proposed a defect detection algorithm for tiny parts that are based on a single short detector network (SSD) and deep learning. Finally, they combined an industrial real-time detection platform with the missed detection algorithm for mechanical parts based on intermediate variables to address the problem of missed detections. They used a 0.8 cm darning needle as the experimental object. The system defect detection accuracy was the highest when the speed of the conveyor belt was 7.67 m/min.

Christian G., et al [5] build process in which multiple images were collected at each build layer using a high-resolution digital single-lens reflex (DSLR) camera. For each neighbourhood in the resulting layer wise image stack, multidimensional visual features were extracted and evaluated using binary classification techniques, i.e. a linear support vector machine (SVM). Through binary classification, neighbourhoods are then categorized as either a flaw, i.e. an undesirable interruption in the typical structure of the material, or a nominal build condition. Ground truth labels, i.e. the true location of flaws and nominal build areas, which are needed to train the binary classifiers, were obtained from post-build high-resolution 3D CT scan data. In CT scans, discontinuities, e.g. incomplete fusion, porosity, cracks, or inclusions, were identified using automated analysis tools or manual inspection. The xyz locations of the CT data were transferred into the layer wise image domain using an affine transformation, which was estimated using reference points embedded in the part. After the classifier had been properly trained, in situ defect detection accuracies greater than 80% were demonstrated during cross-validation experiments.

Lu, et al [6] proposed Deep learning-assisted Real-time defect detection and closed-loop adjustment of additive manufacturing (AM) which are essential to ensure the quality of as-fabricated products, especially for carbon fiber reinforced polymer (CFRP) composites via AM. Machine learning is typically limited to the application of online monitoring of AM systems due to a lack of accurate and accessible databases. In this work, a system is developed for real-time identification of defective regions, and closed-loop adjustment of process parameters for robot-based CFRP AM is validated. The main novelty is the development of a deep learning model for defect detection, classification, and evaluation in real-time with high accuracy. The proposed method is able to identify two types of CFRP defects (i.e., misalignment and abrasion). The combined deep learning with geometric analysis of the level of misalignment is applied to quantify the severity of individual defects. A deep learning approach is successfully developed for the online detection of defects, and the defects are effectively controlled by closed- loop adjustment of process parameters, which is never achievable in any conventional methods of composite fabrication.

Wire and arc additive manufacturing (WAAM) is an emerging manufacturing technology that is widely used in different manufacturing industries. To achieve fully automated production, WAAM requires a dependable, efficient, and automatic defect detection system. Although machine learning is dominant in the object detection domain, classic algorithms have defect detection difficulty in WAAM due to complex defect types and noisy detection environments. Li Wenhao, et al [7] presented a deep learning-based novel automatic defect detection solution, you only look once (YOLO)-attention, based on YOLOv4, which achieves both fast and accurate defect detection for WAAM. YOLO-attention makes improvements on three existing object detection models: the channel-wise attention mechanism, multiple spatial pyramid pooling, and exponential moving average. The evaluation on the WAAM defect dataset shows that our model obtains a 94.5 mean average precision (mAP) with at least 42 frames per second. This method has been applied to additive manufacturing of single-pass, multi-pass deposition and parts. It demonstrates its feasibility in practical industrial applications and has potential as a vision-based methodology that can be implemented in real-time defect detection systems.

III.CONVOLUTION NEURAL NETWORK

The problem at hand pertains to the realm of manufacturing quality control, where the goal is to develop a robust system for Manufacturing Defect Detection using Image Processing and Machine Learning. With the increasing demand for high-quality products, identifying defects in the production line has become paramount. Traditional inspection methods are often labour-intensive and error-prone. This initiative aims to address these challenges by leveraging image processing and machine learning techniques to automatically detect and classify defects in manufacturing processes. The key objectives include reducing production costs, improving product quality, and enhancing the overall efficiency of manufacturing operations, ultimately ensuring customer satisfaction and competitive advantage.

The machine learning model employed in this study is based on transfer learning, utilizing the ResNet50 architecture as shown in Fig1, pre-trained on the ImageNet dataset. ResNet-50 is a convolutional neural network that is 50 layers deep. Detailed Model Component are

- Input Layer- Input images are resized to 256x256 pixels and have 3 channels (RGB).
- Pre-Trained ResNet-50 Backbone- The ResNet-50 architecture serves as the backbone of the model. It consists of 50 layers, including convolutional layers, batch normalization layers, activation layers (ReLU), and skip connections (residual connections).
- Global Average Pooling Layer- After the backbone, a Global Average Pooling 2D layer is added. It reduces the spatial dimensions of the features while retaining important information.
- Dense Layers- Following the Global Average Pooling layer, one or more Dense (fully con nected) layers are added to the model.
- Dropout Layer- A Dropout layer is included to mitigate overfitting by randomly dropping a fraction of input units during training.

- Output Layer- The final output layer is a Dense layer with a single unit and a sigmoid activation function.

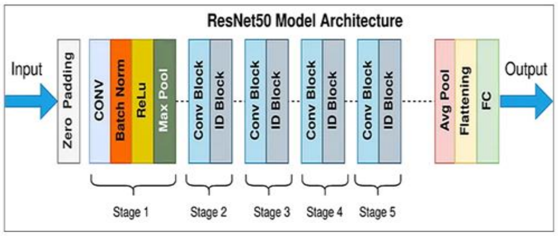


Fig1. ResNet50 architecture

IV.PROPOSED METODOLOGY

The proposed methodology for Manufacturing Defect Detection using Image Processing and Convolutional Neural Network combines cutting-edge techniques to enhance quality control in manufacturing processes. This multifaceted approach consists of several key stages.

First, a comprehensive dataset of defect and defect-free images is collected, ensuring a representative sample of manufacturing conditions. Pre-processing techniques, such as image enhancement and noise reduction, are then applied to standardize and prepare the data for analysis.

Next, state-of-the-art image processing algorithms, like convolutional neural networks (CNNs), are employed to extract meaningful features from the images. These features are then input into machine learning models, such as support vector machines (SVMs) or deep learning networks, to classify and identify defects accurately.

To ensure robustness, the model is trained using cross-validation and fine-tuned with hyperparameter optimization. Regular monitoring and feedback loops are established to continuously improve the system's performance and adapt to evolving manufacturing conditions.

The proposed methodology offers a holistic solution for efficient and accurate manufacturing defect detection, contributing to improved product quality and reduced production costs.

V.DESIGNING & IMPLEMENTATION

The dataset utilized in this study, termed the Casting Defect Dataset as shown in Fig. 3, was obtained from Kaggle, comprising images representing casting molds, encompassing both defective and non-defective instances. Each image in the dataset is assigned one of two classes: defective casting molds (Class 1) or non-defective casting molds (Class 0). The flow to carry out the proposed approach is shown Fig 2.

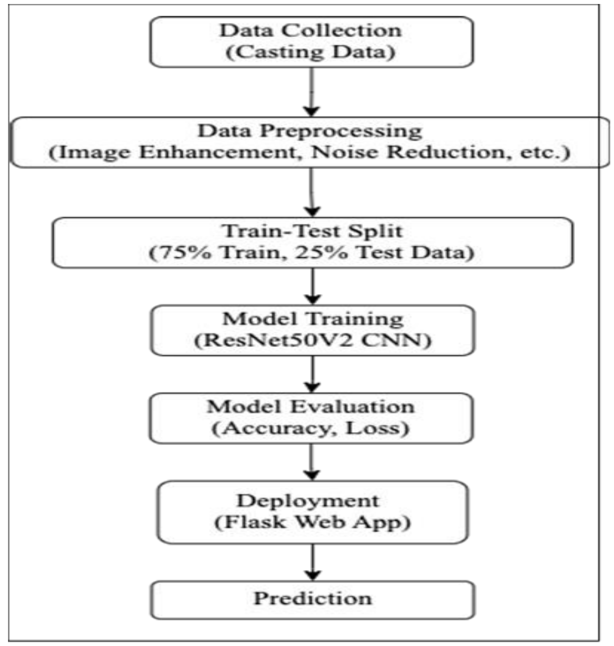


Fig.2 Flowchart

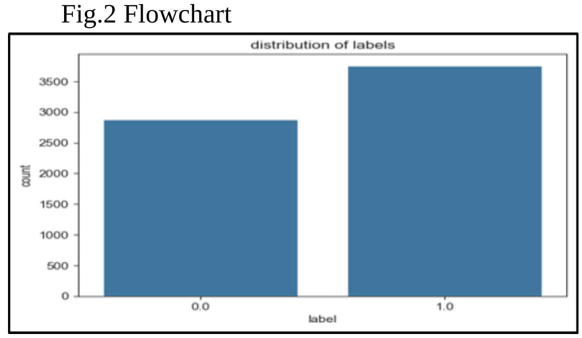


Fig. 3. Distribution of defective and non-defective casting molds

Prior to model training, the images as shown Fig.4 undergo preprocessing to standardize their format and enhance model performance. Images are resized to 256x256 pixels and pixel values are normalized to fall within the range [0, 1].

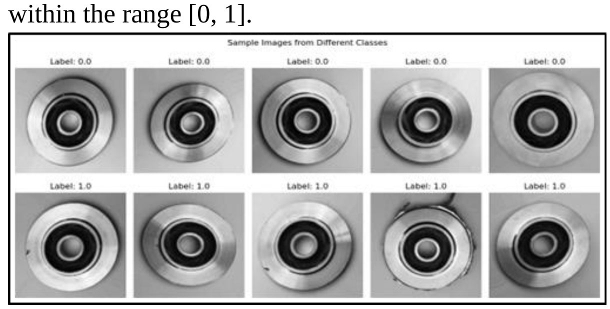
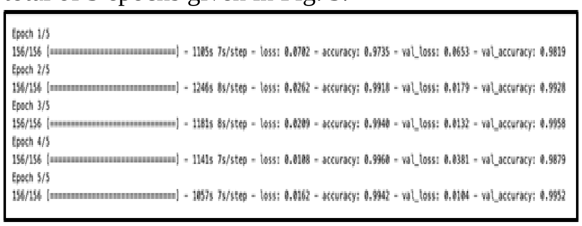


Fig. 4. Sample images of different classes

The machine learning model employed in this study is based on transfer learning, utilizing the ResNet50V2 architecture pre-trained on the ImageNet dataset. The model architecture comprises several key components, including a GlobalAveragePooling2D layer for dimensionality reduction, dense layers with ReLU activation for introducing non- linearity, dropout layers for mitigating overfitting, and a dense output layer with sigmoid activation for producing binary classification predictions.

For model training and evaluation, the dataset is divided into training and testing sets using a 75:25 split ratio. During training, the Adam optimizer is utilized for model optimization, while binary cross-entropy loss function and accuracy metric are employed to evaluate model performance. The model is trained for a total of 5 epochs given in Fig. 5.



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Epoch 1/5
156/156 [==============================] - 1105s 7s/step - loss: 0.0702 - accuracy: 0.9735 - val_loss: 0.0653 - val_accuracy: 0.9819
Epoch 2/5
156/156 [==============================] - 1246s 8s/step - loss: 0.0262 - accuracy: 0.9918 - val_loss: 0.0179 - val_accuracy: 0.9928
Epoch 3/5
156/156 [==============================] - 1181s 8s/step - loss: 0.0209 - accuracy: 0.9940 - val_loss: 0.0132 - val_accuracy: 0.9958
Epoch 4/5
156/156 [==============================] - 1141s 7s/step - loss: 0.0108 - accuracy: 0.9960 - val_loss: 0.0381 - val_accuracy: 0.9879
Epoch 5/5
156/156 [==============================] - 1057s 7s/step - loss: 0.0162 - accuracy: 0.9942 - val_loss: 0.0104 - val_accuracy: 0.9952
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Fig5. Model Training Progress at Epoch [5]

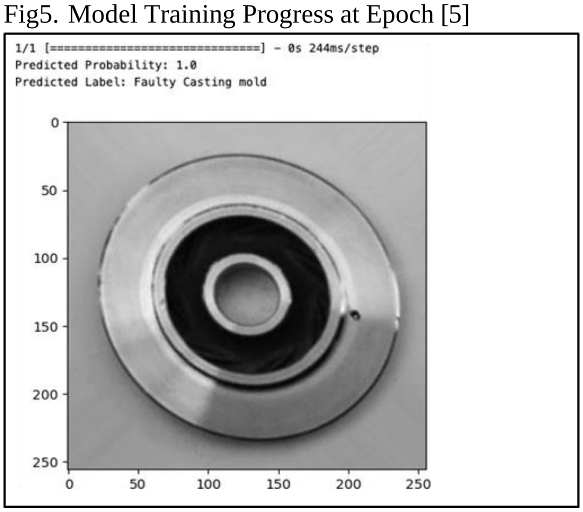

Fig. 6. Prediction of defective casting mold

Finally, the trained model is deployed via a Flask web application for real-time defect detection. Uploaded images are preprocessed before being fed into the model, and predictions are generated to determine whether the casting mold depicted in the image is defective as shown in Fig.5 or non-defective as Fig. 6. This deployment setup enables the integration of automated defect detection

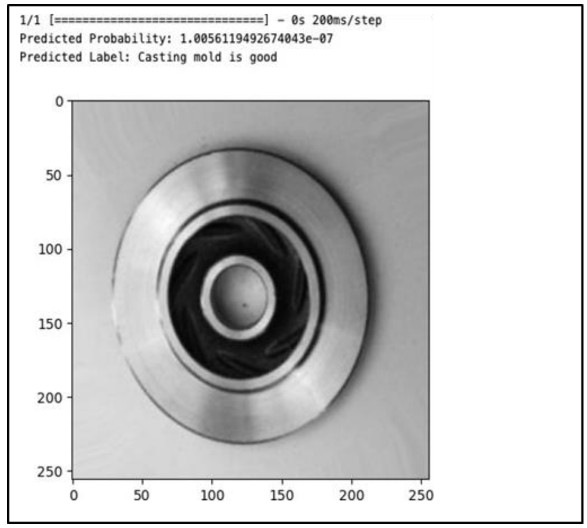

Fig. 7. Prediction of non-defective casting mold

capabilities into manufacturing processes, contributing to enhanced quality control and efficiency.

VI.RESULT & DISCUSSION

The trained model showcased exceptional performance in automating the identification of defects in casting molds, boasting an impressive accuracy rate of approximately 99% on the test dataset. This noteworthy accuracy underscores the model's proficiency in accurately categorizing casting molds as either defective or non-defective as shown in Fig.8 and Fig. 9, thereby highlighting its potential applicability within real-world manufacturing environments.

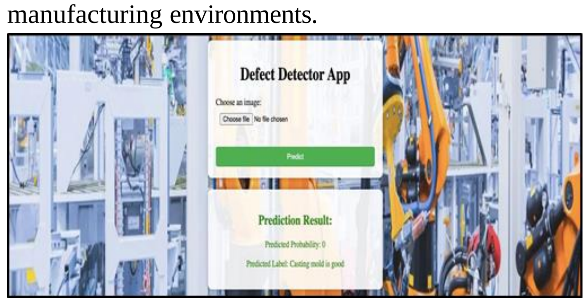

Fig. 8. Model detecting a good casting mold

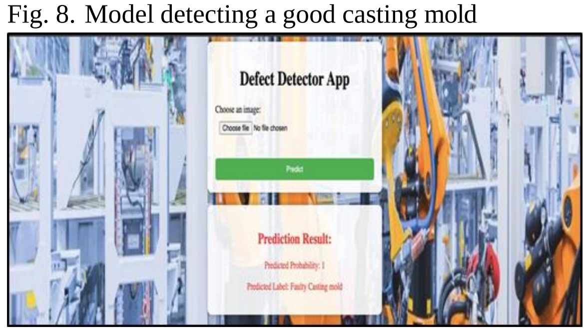

Fig. 9. Model detecting a faulty casting mold

VII. CONCLUSION

In conclusion, the integration of Image Processing and Machine Learning techniques for Manufacturing Defect Detection presents a powerful and promising solution to enhance the quality control processes in manufacturing industries. Through the systematic collection and pre- processing of a diverse dataset, the proposed methodology effectively leverages cutting-edge algorithms to identify and classify defects with high accuracy.

This approach not only significantly reduces the likelihood of faulty products reaching consumers but also streamlines production processes, leading to improved operational efficiency and cost savings. Moreover, the adaptability of the system through continuous monitoring and feedback loops ensures its relevance in dynamic manufacturing environments.

The utilization of this methodology can revolutionize the way manufacturers detect defects, making it a valuable asset in ensuring product quality, reducing waste, and enhancing overall competitiveness. With the ongoing advancements in image processing and machine learning, the future of manufacturing defect detection holds even more promise for further optimization and automation in quality control procedures.

VIII. FUTURE SCOPE

The scope of Manufacturing Defect Detection using Image Processing and Machine Learning is vast and promising, offering numerous opportunities for enhanced quality control and operational efficiency in diverse manufacturing sectors. This approach can be applied across various industries, including automotive, electronics, aerospace, and more.

In the automotive industry, it can aid in identifying defects in vehicle components, ensuring the safety and reliability of vehicles. In electronics manufacturing, it can help identify defects in printed circuit boards, reducing product failure rates. Moreover, the aerospace sector can benefit from the precise detection of defects in critical components, enhancing safety in air travel.

Beyond specific industries, this technology can adapt to various manufacturing processes, making it highly versatile. Its potential to reduce production costs, minimize waste, and enhance product quality positions it as a valuable tool for manufacturers worldwide.

Additionally, ongoing research and development in this field continue to expand its capabilities, enabling the integration of advanced techniques such as real-time defect detection and predictive maintenance. The scope of Manufacturing Defect Detection using Image Processing and Machine Learning is thus wide-reaching, offering substantial potential for improving manufacturing processes across numerous sectors.

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