Structural Anomaly Detection in Advanced Manufacturing Execution Systems

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***Abstract*—Anomaly detection is crucial to ensuring the robustness and reliability of operational systems. Early identification of anomalies and deviations from standard patterns prevents potential failures, enhances decision-making processes, and optimizes overall system performance. This paper investigates image-based structural anomaly detection for manufacturing execution systems utilizing an optimized VGG16 convolutional neural network to identify structural anomalies. The optimized VGG16 model significantly performs binary classification on the test data to distinguish normal and anomalous instances. A comparative analysis with another classifier demonstrates that the optimized VGG16 is notable with high anomaly detection accuracy and has the potential to improve system reliability significantly. Experimental findings on publicly available image-based anomaly datasets demonstrate the efficiency and effectiveness of the proposed technique in identifying anomalies in management execution systems.**

***Index Terms*—Anomaly detection, convolutional neural networks, deep learning, manufacturing execution systems (MESs), optimized VGG16.**

I. Introduction

In recent years, the efficient functioning of management execution systems has become crucial for various industries, including manufacturing, finance, healthcare, and transportation. These systems are pivotal in process automation, resource optimization, and decision-making processes, significantly impacting overall operational efficiency. However, ensuring these systems' robustness and reliability is paramount, as anomalies or deviations from expected behavior can lead to critical failures and financial losses.

Anomaly detection is essential to monitoring and maintaining the manufacturing system, which entails finding occurrences that dramatically vary from anticipated behavior patterns [1]. Machine learning [2] and traditional [3], [4] anomaly detection strategies often depend on statistical or rule-based methods, which may better capture the complex and non-linear patterns present in contemporary management execution systems

To address these challenges, deep learning techniques have emerged as a promising solution for anomaly detection tasks, particularly with the advancement of convolutional neural networks (CNNs) for image-related applications [5], [6]. The CNN architecture proposed by the Visual Geometry Group (VGG) at the University of Oxford, known as VGG16 [7], has garnered significant attention due to its exceptional performance in image recognition tasks. With 16 layers and pre-trained on large-scale image datasets, the VGG16 model possesses powerful feature extraction and representation learning capabilities.

This study explores using the VGG16 model for anomaly detection in manufacturing execution systems. The proposed method fine-tunes the pre-trained VGG16 model for binary classification, distinguishing between normal and anomalous instances. The approach aims to achieve higher accuracy and efficiency by leveraging the model's hierarchical feature extraction capability [8]. Previous research in various domains, such as medical imaging, industrial automation, and manufacturing, has shown the effectiveness of CNNs in anomaly detection [9]–[11]. Additionally, the successful application of transfer learning and fine-tuning with pre-trained CNNs is in tasks like image recognition and object detection [12].

This paper mainly contributes to anomaly detection in manufacturing execution systems by offering a reliable and efficient approach that enhances system reliability and performance. It further examines and validates the efficacy and applicability of the VGG16 for anomaly detection in the product line of the manufacturing execution system through experiments, leveraging a publicly available MVTec LOCO AD dataset [13]. As an exploratory investigation, this study specifically focuses on the following:

1) This study employed an optimized VGG16 to detect structural anomalies in product lines.
2) To evaluate and ascertain the applicability of the optimized VGG16 for anomaly detection in the various products of the manufacturing execution system.
3) Compared the performance of the optimized VGG16 with another classification approach for reliability tests.

The structure of the paper is as follows: Section I is preceded by Section II, which presents a comprehensive literature review of various anomaly detection methods and deep learning-based approaches. Section III details the methodology and data preparation. Section IV provides insights into the experimental setup, evaluation metrics, and results. Section V concludes the paper, highlighting limitations and future direction.

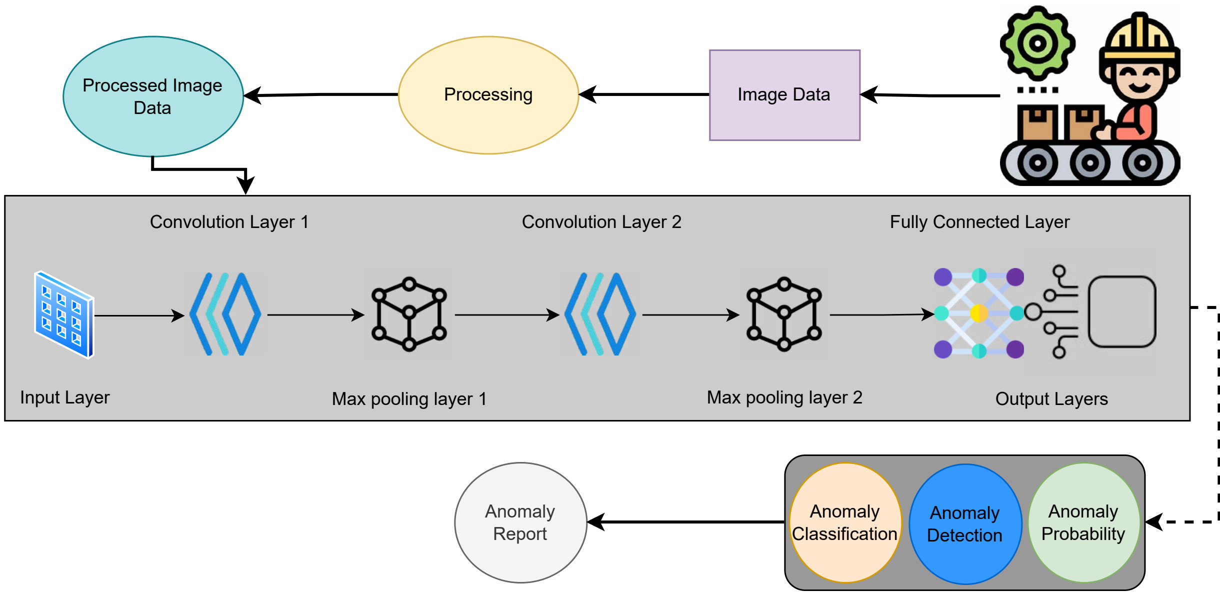

Fig. 1. Process flow of the optimized VGG16 for structural anomaly detection in the product line of the MES

II. Related Work

Anomaly detection in manufacturing execution systems has been extensively explored using machine learning and deep learning techniques. Convolutional neural networks have shown promise in capturing complex patterns in various domains. Rajaraman et al. [9] utilized pre-trained CNNs as feature extractors for malaria parasite detection in medical imaging, showcasing its potentiality in detecting anomalies.

H. Benaddi et al. [10] proposed a novel anomaly detection framework for the Industrial Internet of Things using distributional reinforcement learning and generative adversarial networks (GANs). Their approach combined distributional reinforcement learning to model normal sensor data probability distribution and GANs to generate synthetic data resembling the normal distribution. The system effectively detects anomalies by identifying significant deviations from the learned distribution, demonstrating superior performance compared to traditional methods. Furthermore, transfer learning with pre-trained CNNs has been effective in image-related tasks [12]. The adoption of CNN architectures, such as VGG16, has significantly improved image recognition accuracy, extending their application to anomaly detection [11].

Y. Jiang et al. [11] demonstrate that deep learning-based anomaly detection accurately classifies industrial product anomalies in real-time high-speed production scenarios. Despite their promising results, deep learning methods still have limitations, including the need for abundant labeled data and higher computational complexity. Thus, overcoming these limitations requires innovative techniques that can balance accuracy and efficiency in anomaly detection, particularly in manufacturing execution systems.

In summary, the literature showcases the potential of CNNs in anomaly detection for manufacturing execution systems. Pre-trained CNN models like VGG16 demonstrate exceptional feature extraction capabilities in detecting structural anomalies, but further research is needed to enhance their efficiency and broader applicability in real-world applications.

III. Methodology

This section explains the optimized VGG16 model for anomaly detection. Fig. 1 illustrates the system model architecture and process flow.

A. Manufacturing Execution System Product Line

In the manufacturing execution system, the product line includes a range of applications and modules designed to address various aspects of the manufacturing process. It is aimed at flexibility and scalability, allowing for selecting and configuring modules that best suit specific production needs. It enhances operational efficiency, reduces costs, improves product quality, and makes data-driven decisions to optimize manufacturing processes. Monitoring and detecting anomalies is essential to maintain operational efficiency and maximize profit [1], [3].

B. VGG16 Model Architecture Hyper-parameter Optimization for Anomaly Detection

The VGG16 model, a deep convolutional neural network known for image classification, is adapted in this study for anomaly detection. Although the VGG16 model focuses on image classification, it is adapted with fine-tuned parameters for efficient anomaly detection in the production line of the manufacturing execution system. The employed pre-trained 16 layers VGG16 model was fine-tuned, initializing weights from ImageNet for binary classification between normal and anomalous structural instances. Extending the model with additional layers for fine-tuning includes a Dense layer of

128 units with ReLU activation and another Dense layer with softmax activation for the final classification. The model compilation employed 'sparse_categorical_cross-entropy' loss, Adam optimizer with a learning rate 0.001. Modifying the VGG16 model enables efficient training and validation for image-based anomaly detection in the production line of the manufacturing execution system. To enhance the model generalization, the re-scaling approach normalized the data by scaling the image pixel values by dividing the pixel values by 255 to a range between 0 and 1 to improve the training performance of the optimized VGG16 model. The model was trained for 10 epochs with a batch size of 32 and a dropout rate of 0.5 to prevent over-fitting.

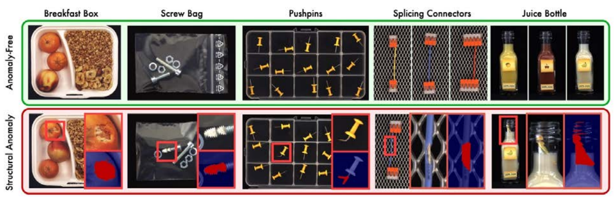

Fig. 2. A view of the five classes of the evaluated MVTec LOCO AD dataset

IV. Experimental Results and Discussion

A. Dataset Description and Simulation Setup

The MVTec LOCO AD dataset [13] was obtained from real-world industrial inspection scenarios and consists of 3644 training and validation images and 1725 test images. The training set comprises defect-free images, while the test set includes defective and defect-free images of various object categories such as breakfast boxes, juice bottles, pushpins, screw bags, and splicing connectors. During data processing, the images were categorized based on the object type, and the test set contained anomalous samples with structural defects like distorted object parts or defects manifesting without certain object parts. All images were resized to 224x224 pixels to ensure data quality, as depicted in Fig. 2.

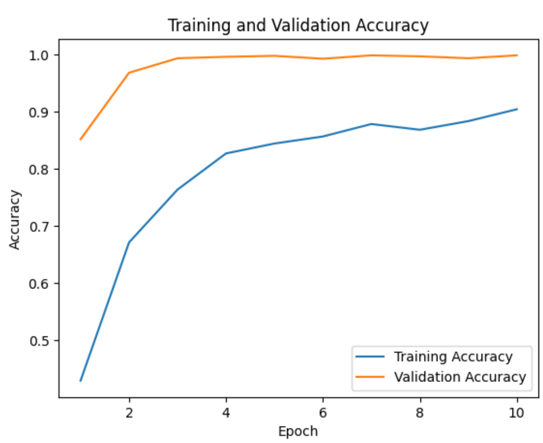

Fig. 3. Accuracy graph of the optimized VGG16 model for structural anomaly detection

B. Optimized VGG16 Performance and Evaluation Metrics

The model's performance was assessed using various evaluation metrics, including accuracy, precision, recall, and f1-score. The confusion matrix and the area under the receiver operating characteristic curve (AUC-ROC) curve enabled measuring the model performance to evaluate its classification capability. The optimized VGG16 model demonstrated exceptional performance on the test dataset, as shown by the train-validation graph in Fig. 3. Consequently, Fig. 4 is the confusion matrix illustrating the classification ability of the different images by the optimized VGG16. The classification report presented in Table I provides valuable insights into the ability of the optimized VGG16 to detect structural anomalies within the five image classes.

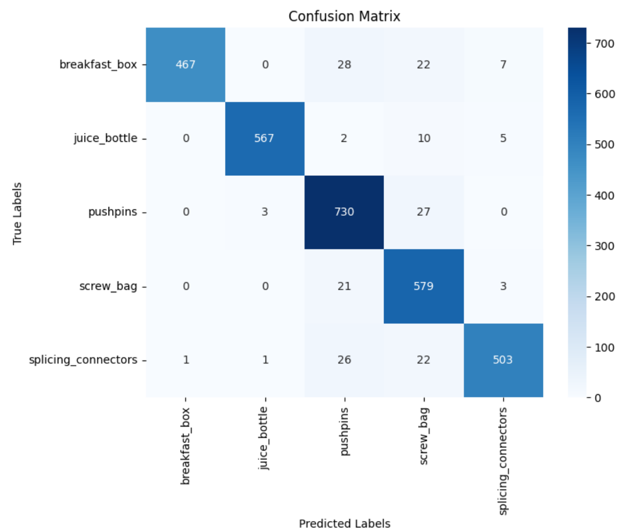

Fig. 4. Confusion Matrix of the optimized VGG16

TABLE I
Classification Report of the Optimized VGG16 Model on the Various Image Classes

Class Name	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)	Accuracy (%)
Breakfast Box	100	89	94	98	94
Juice Bottle	99	97	98	99	94
Pushpins	90	96	93	96	94
Screw Bag	88	96	92	97	94
Splicing Connectors	97	91	94	98	94
Avg_Accuracy	94.8	93.8	94.2	97.2	94

The comparative analysis Table II of the performance of the support vector machines and the optimized VGG16 shows a significant performance by the optimized VGG16 for image-based structural anomaly detection. The optimized VGG16 achieved a higher detection accuracy of 94%, demonstrating its ability to accurately classify normal and anomalous instances among the five object categories.

The classification report displayed high precision, recall, and F1 scores for each class, confirming the model's efficacy in identifying anomalies. Specifically, the highest precision of 100% was achieved for the juice bottle, while the splicing connectors exhibited the highest recall of 97%. The ROC curves were plotted for each class, illustrating the model's true

TABLE II
COMPARATIVE ANALYSIS REPORT OF THE OPTIMIZED VGG16 AND THE SVM

Performance Evaluation Metrics	Optimized VGG16	Support Vector Machines
Accuracy (%)	**94**	64
Recall	**93.8**	64
Precision	**94.8**	79
F-score	**94.2**	70
ROC-AUC	**97.2**	69

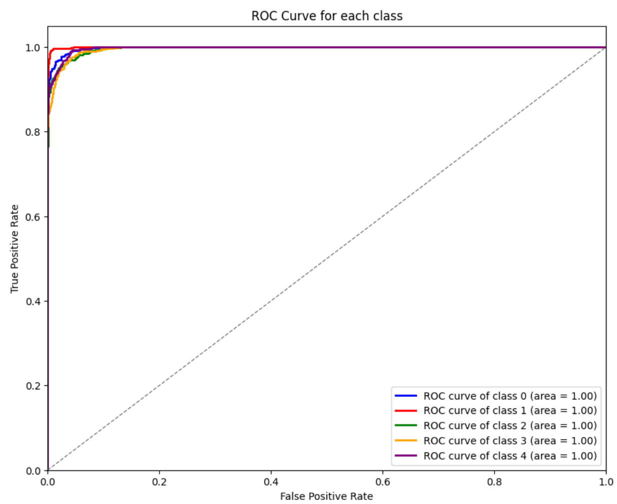

Fig. 5. The AUC-ROC curve of the optimized VGG16 model for each image class.

positive rate against the false positive rate. The area under the ROC curve (AUC) values ranged from 96% to 99%, with an average AUC of 97% across all classes, as shown in Fig. 5. Thus indicating the model's ability to discriminate between normal and anomalous instances effectively. Overall, the experimental results validate the proposed anomaly detection approach, demonstrating its robustness and potentiality for the production line of the manufacturing execution systems.

V. CONCLUSION

In this study, we investigated an image-based anomaly detection for the production line of the manufacturing execution system utilizing an optimized VGG16 model. The optimized VGG16 model demonstrated a significant performance for anomaly detection in accuracy, precision, recall, f-score, and ROC-AUC for each image class. The AUC-ROC curves further validated the model's discriminating capabilities. The main findings highlight the proficiency of deep learning techniques, specifically VGG16, in capturing complex patterns and hierarchical features for accurate structural anomaly detection. The proposed system's robust performance offers valuable insights into enhancing system reliability and optimizing resource allocation in manufacturing execution systems. The potential impact of the optimized VGG16 for anomaly detection is significant. By proactively identifying anomalies and deviations from normal behavior, the system enables timely intervention and preventative measures, leading to improved decision-making and streamlined operations. The increased efficiency and reduced downtime translate into cost savings and enhanced organizational productivity. Overall, the study's contributions lie in presenting a reliable and efficient approach for anomaly detection in manufacturing execution systems, providing a solid foundation for implementing real-world applications with enhanced performance and reliability.

VI. ACKNOWLEDGMENT

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