Deep Learning for Multivariate Anomaly Detection in Advanced Manufacturing Execution Systems

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***Abstract*—Efficient, time-sensitive, and precise predictions of dynamic scenarios is crucial for smooth industrial processes and production. This study underscores the importance of automating the detection and prediction of anomalies in manufacturing execution systems (MES) using artificial intelligence algorithms. A sophisticated deep learning (DL) model (YOLOv8) was adopted as the underlying cognitive prediction model for the MES. The dataset used comprises 1700 samples of the MVtec dataset in three categories: good, logical anomaly, and structural anomaly. The result shows that real-time, efficient, and cost-effective multivariate anomaly detection in MES is feasible using YOLOv8n achieving a 92% precision, 94% recall, 90.5% F1-score, 0.6 loss, and 29.7ms latency prediction performance.**

***Index Terms*—Anomaly Detection, Deep learning, Manufacturing Execution Systems, YOLO,**

I. Introduction

Manufacturing Execution Systems (MES) serve critical functions such as production control, data acquisition, and fault detection and segmentation. Specifically, fault detection constitutes a vital aspect of MES operations, often categorized as anomaly detection. This involves the real-time identification of irregularities or faults within the production process that have the potential to impact product quality or efficiency. Subsequent responsive actions are then taken to address these anomalies promptly. Several authors have investigated different anomaly detection strategies in MES, such as traditional/observatory approach [1], machine learning [2], and deep learning [3] approaches.

Current anomaly detection methods rely primarily on textural information, which limits the accuracy of categorized aberrant samples. Texture information is insufficient to fully depict the pattern of anomalies, particularly logical abnormalities. In [4], authors discuss structural anomaly detection, while [5] explains both structural and logical anomalies using a balanced dataset. To overcome this challenge, this work focuses on enhancing the MES operations through efficient and cost-sensitive prediction of faults using the You Only Look Once version 8 (YOLOv8) paradigm to extract complex texture features of MES objects. The YOLO architecture has been used for multivariate pattern object recognition and classification in many applications [6], [7] with optimal results.

II. Methodology

The overall system model is shown in Fig. 1. The process starts with data collected from the factory machinery. The system extracts features from the data. The adopted machine-learning model (YOLOv8) is then used to analyze the features and identify anomalies. The model then outputs classification results. If the model detects an anomaly, the system triggers an alert. A technician is notified and takes steps to repair or address the anomaly. If no anomaly is detected, the system continues to monitor the machinery.

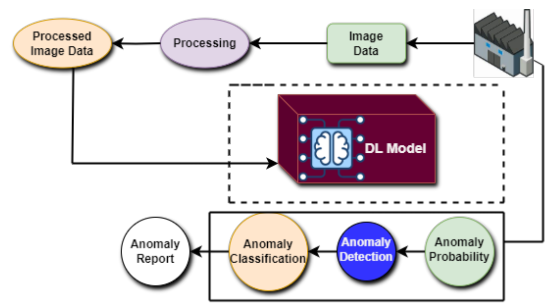

Fig. 1. System Architecture of the DL-enabled MES complex texture anomaly detection.

The YOLOv8 architecture uses a modified CSP Darknet53 backbone. Through feature pooling into a fixed-size map, a spatial pyramid pooling fast (SPPF) layer speeds up computation. SiLU activation and batch normalization are present in every convolution. The head is decoupled to process objectness, classification, and regression tasks independently. To satisfy the demands of diverse scenarios, YOLOv8 is available in the following size models: nano (n), small (s), medium (m), large (l), and extra-large (x), depending on the scaling factor. In this study, YOLOv8n was adopted as the underlying AI algorithm being the light-weight version of the YOLOv8 series.

The dataset comprises 1700 data samples in three categories: good, structural anomaly, and logical anomaly, and was collated especially to show production in industrial scenarios. Before feature engineering, data underwent systematic collection, preprocessing, and cleaning to enhance model predictive capabilities. Exploratory analysis uncovers patterns, leading to model development and validation using YOLOv8n deep learning. The data was divided into 70 percent training, 20 percent testing, and 10 percent validation. The experimental simulation platform was run in a Python environment using the PyTorch 1.10 framework on a computer running Windows 10 with the following specifications: Intel(R) Core(TM) i5-8500

CPU @ 3.00GHz, 6Core(s), NVIDIA GeForce GT 1030, GPU CUDA:0 (Tesla K80, 11441.1875MB), and 36GB RAM.

III. Results

The anomaly detection and prediction performance capacity of the model was validated based on mean average precision, recall (sensitivity), rationale behavior (F1-score), error cost (loss function), and inference time (latency).

F1-score (F1): examines the model's rational behavior.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{1}$$

SCYLLA IoU (SIoU) Loss: is an Intercession of Union (IoU)-based loss function used to estimate the bounding box localization accuracy for object classification and detection. The formula for SIoU is given as;

$$Box\_loss(L_{box}) = 1 - IoU + \frac{\triangle + \Omega}{2} \tag{2}$$

where $\triangle$ is distance cost; and Ω is shape cost.

The predictive reliability performance of the adopted model for anomaly detection is summarized in Table I.

TABLE I
Predictive Reliability Performance of DL-based Anomaly Detection

Epoch	Precision (%)	Recall (%)	Box_loss
16	92.0	94.0	0.8
32	80.2	81.4	0.7
64	78.8	79.4	0.6

The values in Table I reveal that YOLOv8n can adequately detect and classify each class of the MES data, as anomaly patterns increase with minimal prediction error. At 16 epochs, 92% precision, 94% sensitivity, and 0.8 loss were achieved by the adopted model as against 0.6 loss when there was an increase in the anomaly. This implies that with an increase in the texture feature of anomalies in the MES production line, the underlying DL model can reliably decipher the good objects from the anomalies.

Furthermore, Table II compares the performance effectiveness and efficiency of YOLOv8n with other related methods.

TABLE II
Performance Evaluation with State-of-the-Art Models

Model	Precision (%)	Recall (%)	F1-score (%)	Time (ms)
VGG-16 [4]	94.8	93.2	94.2	**
YOLOv5s	80.2	81.4	82.0	25.2
YOLOv8n	**92.0**	**94.0**	**90.5**	**29.7**

Across all the metrics, YOLOv8n achieved a better predictive performance capacity in anomaly detection as objects' texture information increases with a precision of 92%, sensitivity of 94%, rationality (F1-score) of 90.5%, YOLOv5s and VGG-16 used by authors [4]. This implies that the dynamic variability of the anomalies in the MES production line can be sufficiently handled by the adopted underlying DL model

Lastly, the performance efficiency of the models in terms of prediction timeliness for anomaly detection is shown in Fig 2.

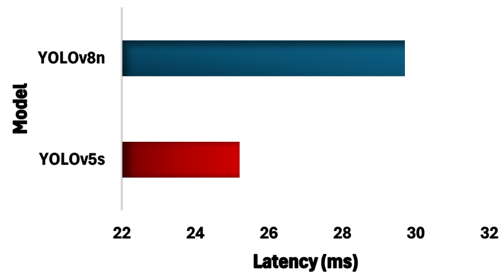

Fig. 2. DL Models Prediction Timeliness for Anomaly Detection in MES Production Line.

The result from the chart indicates that timely and cost-effective prediction of anomalies in advanced MES production lines is feasible, with the YOLOv5s achieving a prediction latency of 25.2 ms and 29.7 ms for YOLOv8n respectively.

IV. Conclusion

This study assesses the effectiveness of a deep learning model for predicting anomalies in MES to optimize decision-making. The result validates that the application of DL models can enhance multivariate anomaly detection as texture information increases with exact precision, timeliness, and cost-effectiveness. Future work will seek to expand the dataset and modify the underlying architecture for higher predictive performance. Additionally, the research will explore integrating real-time data streams to further improve the responsiveness and accuracy of anomaly detection.

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