Data Visualization and Fault Detection Model for Sputtering Process Monitoring

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ABSTRACT

This paper introduces a real-time system for data visualization and fault detection specifically tailored for industrial sputtering processes, focusing on monitoring parameters such as deposition rate, film thickness, material types (Ti, Ag, Ni), and overall process status. The project's primary goals are to model multi-level anomaly outliers to detect potential OCR errors and process deviations, implement a real-time embedded vision system for automated data acquisition from the equipment's display (achieving high accuracy with YOLO and PaddleOCR), and deploy a complete monitoring application featuring real-time visualization and post-process analysis. Data acquisition is carried out using a high-resolution camera, where YOLO achieves 99.5% mAP@0.5 in supervised detection of visual indicators, and PaddleOCR attains 99.57% accuracy in extracting numerical parameters. Preprocessing incorporates a median filter to suppress noise, while DBSCAN identifies sudden OCR fluctuations and linear regression models parameter trends. The postprocessed data are stored in structured CSV files. By integrating robust supervised and unsupervised learning techniques with data science methodologies, the proposed solution ensures reliable operational monitoring, enables early anomaly detection, and supports predictive maintenance strategies in industrial settings.

Keywords: Machine learning, Sputtering process Monitoring, Real-time Fault detection, Embedded Vision, Optical Character Recognition (OCR), Anomaly Detection

INTRODUCTION

In the era of Industry 4.0, rapid and reliable sensor data acquisition is essential for predictive maintenance, anomaly detection, and process optimization in modern manufacturing systems [1][2]. In semiconductor and thin-film coating applications, sputtering processes require precise monitoring of critical parameters such as electrical power, deposition rate, and film thickness. These processes often involve materials like titanium (Ti), silver (Ag), and nickel (Ni), each exhibiting unique deposition characteristics. However, many legacy sputtering machines lack built-in remote data access, making hardware upgrades difficult or impractical.

This paper presents a vision-based monitoring system that captures process parameters directly from sputtering machine display panels using YOLO-based object detection [3][4] integrated with Optical Character

Recognition (OCR). The system leverages the computational capability of the NVIDIA Jetson Orin Nano to perform real-time image processing and efficiently extract key operational data. First, YOLO detects and classifies visual indicators on the display, after which OCR extracts numerical parameters such as electrical power, deposition rate, and film thickness. To enhance data reliability, median filtering is applied to suppress noise, followed by the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm for anomaly detection. This helps distinguish genuine process faults from abrupt OCR fluctuations. Linear regression is then used to model deposition trends, enabling fault identification and trend analysis. All extracted and time-stamped data are stored n structured CSV files, supporting both real time fault detection and data-driven decision making.

The key contributions of this research are threefold: (1) the development of an embedded, non-invasive vision system for real-time data acquisition from sputtering equipment; (2) the implementation of a multi-stage anomaly detection framework that integrates OCR error screening with machine fault modeling; and (3) a comprehensive performance evaluation of the detection models, OCR engines, and anomaly detection methods to establish benchmarks for accuracy, efficiency, and robustness.

Problem Statement

A major challenge in modern manufacturing is the difficulty of obtaining real-time process data from legacy equipment, where hardware modification is often impractical, costly, or risk disrupting machine performance. This work addresses this issue in sputtering systems, which typically lack direct digital access to critical sensor information. To overcome this limitation, this work proposes a non-invasive monitoring approach deployed on an NVIDIA Jetson embedded platform that uses Optical Character Recognition (OCR) to extract process parameters directly from the equipment's display panels. However, reliance on a vision-based method introduces an inherent risk: inaccurate OCR readings may trigger false alarms or, conversely, mask actual machine faults. Therefore, a central component of this research is the integration of robust data validation and error-handling mechanisms to ensure the reliability and integrity of the captured data. This enables accurate real-time visualization and supports proactive fault detection.

LITERATURE REVIEW

1. Overview of Sputtering Deposition Processes

Sputtering is a widely adopted Physical Vapor Deposition (PVD) technique used for fabricating thin films with precise control over composition, thickness, and uniformity. The process is based on momentum transfer, in which energetic ions, typically generated from an argon plasma, bombard a solid target material. As a result of these collisions, atoms are ejected from the target surface and subsequently condense on a substrate, forming a thin film, as illustrated in Figure 1. This mechanism, commonly referred to as cathode sputtering, supports the deposition of metals, alloys, semiconductors, and dielectric materials with strong adhesion and uniform coverage [5][6].

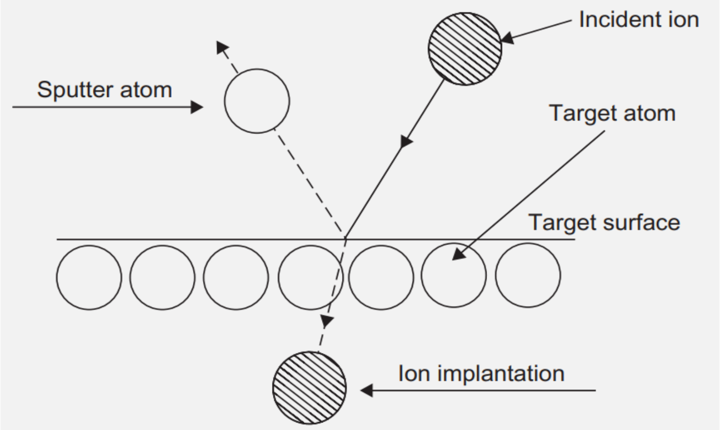

Figure 1: Physical sputtering processes [6]

Several sputtering configurations have been developed to accommodate different materials and process requirements. DC diode sputtering employed a constant voltage between the cathode and anode and is primarily suitable for conductive targets. RF sputtering extends the technique to insulating materials by alternating the electric field to prevent charge accumulation. Magnetron sputtering, shown in Figure 2, further enhances plasma density through magnetic confinement, leading to higher deposition rates, improved target utilization, and better film quality [7][8][6]. Due to these advantages, magnetron sputtering is widely used in semiconductor and industrial coating applications.

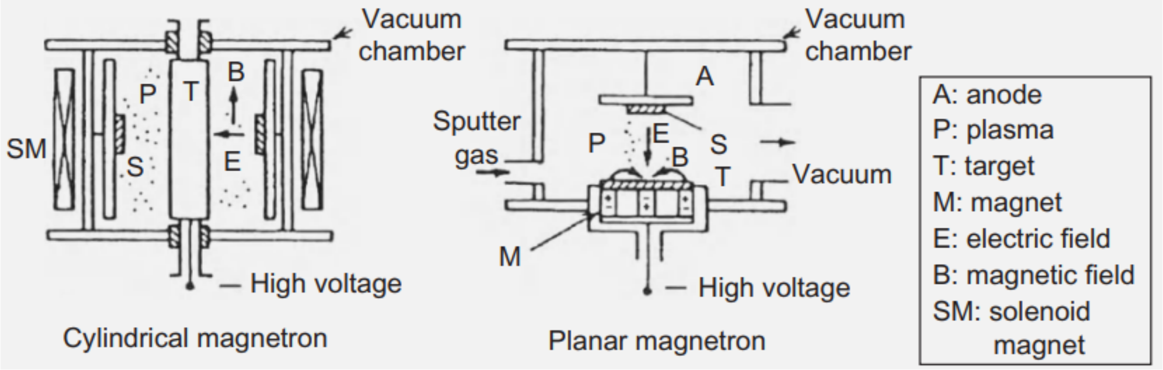

Figure 2: Magnetron sputter deposition systems [6].

2. Critical Process Parameters for Sputtering Process Monitoring

Effective monitoring of sputtering processes relies on continuous observation of key operational parameters that directly influence film quality and process stability. Modern sputtering systems typically display real-time values for electrical power, deposition rate, accumulated film thickness, and overall process state. Together, these parameters provide a comprehensive representation of system behavior during deposition [9].

Electrical power, measured in watts (W) or kilowatts (kW), determines the ion bombardment energy and directly affects the sputtering yield. Stable power delivery is essential for consistent film growth, while power fluctuations may indicate plasma instability, target degradation, or electrical faults.

The deposition rate represents the speed at which material accumulates on the substrate and is commonly expressed in angstroms per second (Å/s) or nanometers per minute (nm/min). This parameter is influenced by applied power, chamber pressure, target condition, and plasma density. Real-time monitoring of deposition rate enables early detection of abnormal process behavior and facilitates process optimization.

Film thickness corresponds to the cumulative deposited layer and is obtained by integrating the deposition rate over time. It is typically expressed in angstroms (Å/s) or nanometers (nm). Accurate thickness monitoring is crucial to meeting design specifications and ensuring timely process termination [10]. Table 1 summarizes the key process parameters commonly monitored in sputtering systems.

Table 1: Key Process Parameters of the Sputtering Machine

Parameter	**Units**	**Typical Range**
Power	Percentage (%)	0-100 %
Deposition Rate	Angstrom per second (Å/s)	0.1-50 Å/s
Film Thickness	Angstrom (kÅ)	0-3 kÅ
Process State	Text/Number	Various states

3. Data Visualization for Industrial Process Monitoring

Data visualization plays a vital role in industrial process monitoring by transforming raw numerical data into interpretable visual representations. In manufacturing environments, real-time visualization of process parameters enables operators to quickly identify trends, deviations, and abnormal behavior that may otherwise go unnoticed in numerical displays alone.

In sputtering systems, graphical visualization of power, deposition rate, and thickness profiles can reveal gradual drifts, sudden spikes, or irregular fluctuations associated with process faults. Prior studies have demonstrated that visual dashboards improve situational awareness, reduce operator response time, and support data-driven decision-making in advanced manufacturing systems [11].

4. Optical Character Recognition for Industrial Data Acquisition

Optical Character Recognition (OCR) is a key enabling technology for extracting textual and numerical information from visual sources, such as equipment displays and control panels. While OCR has been extensively studied in applications like document digitization and Automatic License Plate Recognition (ALPR), recent research has increasingly focused on its application in industrial monitoring and automation [12][13].

In industrial contexts, OCR enables non-invasive data acquisition from legacy equipment that lacks digital communication interfaces. Kim et al. [16] demonstrated a low-cost OCR-based system using Tesseract to extract real-time operational data from CNC machine displays. Similarly, Kaur et al. [17] proposed an Industrial Internet of Things (IIoT) architecture incorporating OCR, achieving recognition accuracy above 97% under controlled conditions.

However, OCR performance remains sensitive to environmental factors such as illumination variation, display reflections, font diversity, and image noise [14]. Leaning-based OCR methods, including neural-network-based classifiers, have been shown to outperform traditional template-matching approaches by adapting to diverse character styles and imaging conditions [12][15]. These findings support the feasibility of OCR as a reliable data acquisition method for real-time sputtering process monitoring.

5. Fault Detection and Anomaly Detection in Sputtering Processes

Fault detection in sputtering processes is essential for maintaining film quality, reducing material waste, and preventing equipment damage. Traditional approaches often rely on rule-based thresholds or operator expertise, which may fail to detect subtle or evolving faults. Consequently, data-driven anomaly detection techniques have gained increasing attention in recent literature.

Clustering-based methods such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) are well suited for identifying abnormal process behavior without requiring labeled fault data [18]. DBSCAN can distinguish normal operating clusters from noise points representing potential faults. However, quantitative performance evaluation is necessary to assess detection reliability. Common statistical metrics used in anomaly detection include precision, recall, F1-score, and false alarm rate, which measure the accuracy and robustness of fault identification.

Regression-based models, such as linear regression, are frequently employed as baseline predictors of expected process behavior. Deviations between predicted and observed values can be interpreted as anomalies. To ensure meaningful interpretation, confidence intervals, residual analysis, and statistical thresholds are typically applied to quantify deviation significance. Prior studies emphasize that combining visualization with statistically validated anomaly detection enhances interpretability and operator trust in intelligent monitoring systems.

METHODOLOGI

1. System Overview

The proposed monitoring system follows a structured workflow consisting of data acquisition, data preprocessing, and data modeling, as illustrated in Figure 3. The system is designed to operate in a non-invasive manner by leveraging computer vision and data-driven analytics to monitor critical sputtering process parameters in real time. The primary parameters of interest include electrical power, deposition rate, and film thickness.

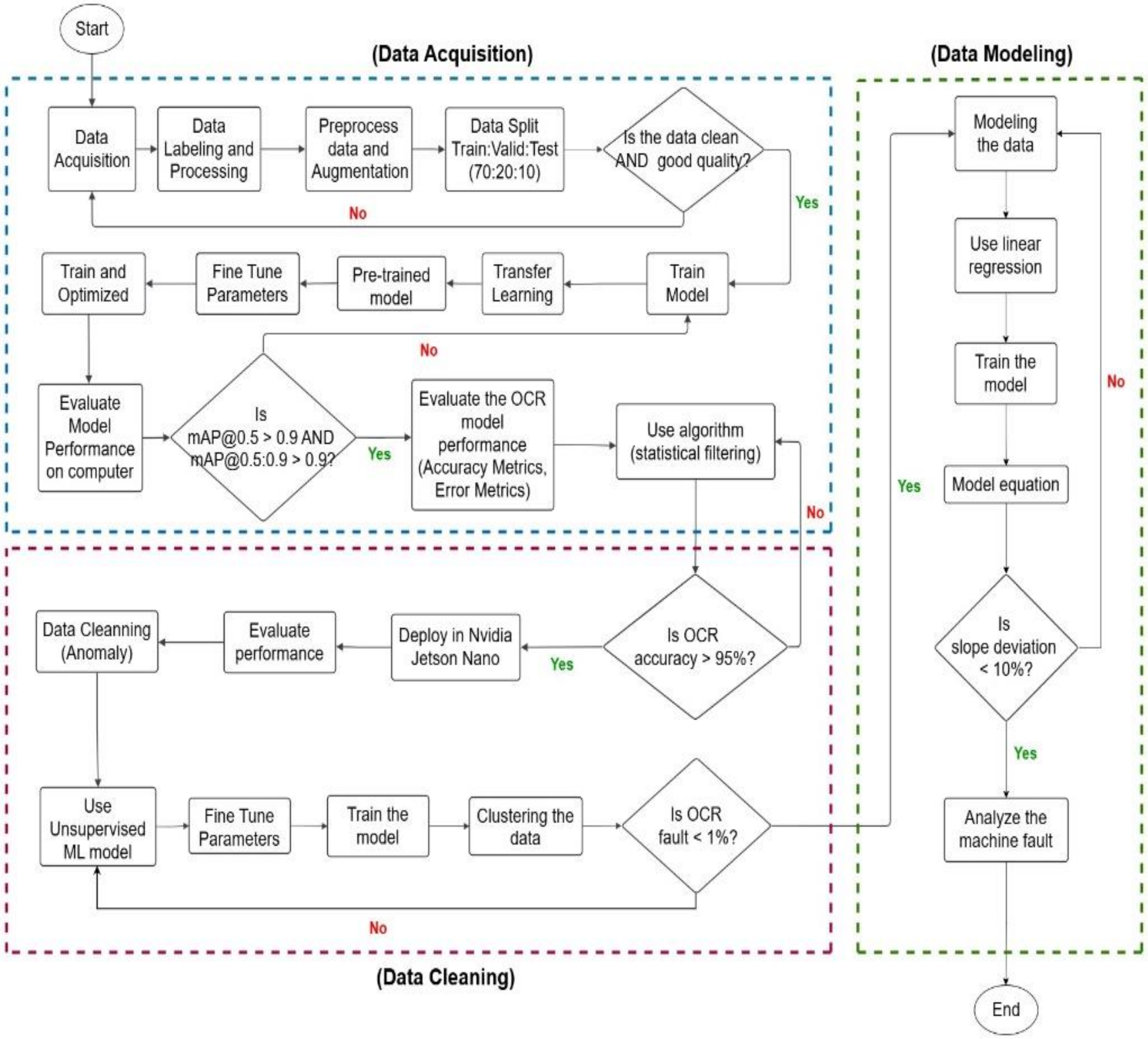

Figure 3: Flow Chart

2. Data Acquisition and Visual Parameter Localization

Real-time images of the sputtering machine's display panel are captured using a high-resolution industrial camera mounted at a fixed position to ensure consistent viewing geometry. The camera continuously records images under normal operating conditions, capturing numerical indicators corresponding to key process parameters.

To localize and identify these indicators, the YOLO (You Only Look Once) object detection framework is employed as shown in Figure 4. YOLO is selected due to its real-time inference capability and high detection accuracy. The model detects predefined regions of interest (ROIs) corresponding to electrical power, deposition rate, and film thickness displays.

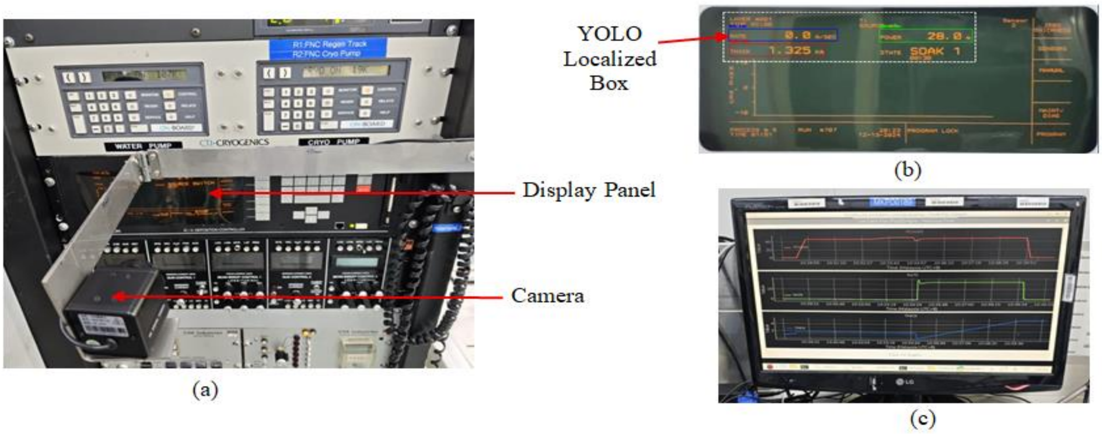

Figure 4: (a) Screenshots of sputtering machine display panel with YOLO detection outputs, (b) illustration of bounding box localization and class labels for each monitored parameter, (c) data presented in real-time graph.

3. Dataset Preparation and Model Training

A custom dataset was constructed specifically for this study. The dataset was divided using an 80:10:10 ratio, consisting of 5046 training images, 644 validation images, and 656 testing images, as shown in Figure 5.

Transfer learning was applied using pre-trained YOLO weights to accelerate convergence and improve generalization. Fine-tuning was conducted on the custom dataset to adapt the model to the specific visual characteristics of the sputtering machine display. The training configuration is summarized in Table 1.

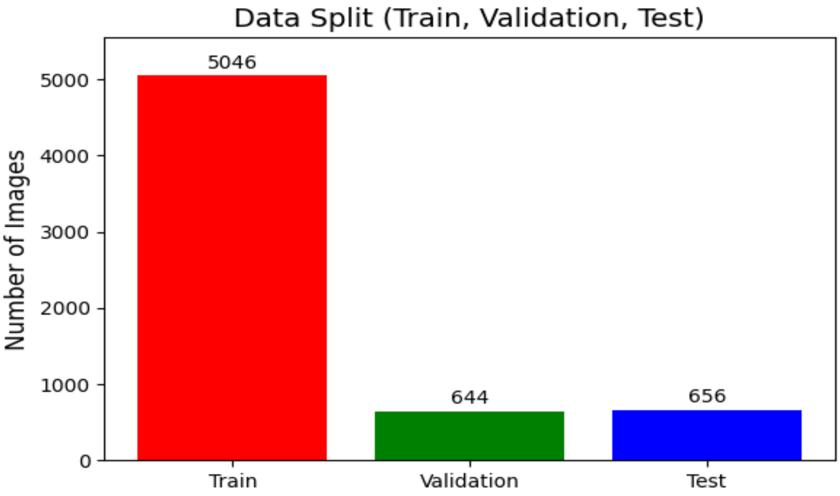

Figure 5: Data Split (Train, Validation, Test)

Model performance was evaluated using standard object detection metrics, including precision, recall, and mean Average Precision (mAP@0.5), to ensure robust and accurate detection prior to deployment.

Table 1: YOLO Training Configuration Parameters

Training Parameters	**Parameters**
Task specification	detect
Model	yolo11s.pt
Dataset location	{dataset.location}/data.yaml

Number of epochs	100
stImage size (imgsz)	640, 480
Batch size	16
Optimizer	AdamW
Learning rate	002
Early stopping	10
Weight decay	0.005

4. OCR-Based Data Extraction and Preprocessing

Following object detection, the localized ROIs are passed to the Optical Character Recognition (OCR) module for numerical value extraction. OCR processing includes a preprocessing pipeline designed to improve recognition accuracy under varying illumination and display conditions. The preprocessing steps include conversion to grayscale, adaptive thresholding to enhance text contrast, noise reduction using median filtering, and morphological operations to refine character boundaries.

Tesseract OCR is employed for numerical recognition, with customized character whitelists and confidence thresholds to reduce misclassification. OCR outputs with confidence scores below a predefined threshold are discarded or flagged for reprocessing.

5. Anomaly Detection Using DBSCAN

To detect abrupt abnormalities in the sputtering process, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is applied to the OCR-extracted numerical data. DBSCAN is well suited for this application due to its ability to identify outliers without requiring labeled fault data.

5.1. Parameter Selection for DBSCAN

The DBSCAN parameter ε (epsilon) and minPts were selected based on empirical analysis and domain knowledge. The ε value was determined using a k-distance plot, where the knee point indicates a suitable neighborhood radius. The minPts parameter was set to 4, following common practice for low-dimensional industrial datasets.

These parameters enable DBSCAN to form dense clusters representing normal operating conditions while labeling isolated points as anomalies.

5.2. Statistical Evaluation of Anomaly Detection

Anomaly detection performance was quantitatively evaluated using precision, recall, and F1-score. Ground truth labels were established through expert inspection of process logs and corresponding visual trends. Precision measures the proportion of correctly identified anomalies, while recall evaluates the system’s ability to detect actual faults. The F1-score provides a balanced assessment of detection accuracy.

6. Trend Analysis Using Linear Regression

In addition to detecting abrupt faults, linear regression models are employed to monitor long-term trends in process parameters such as deposition rate and film thickness. Regression models are trained on historical normal-operation data to establish baseline behavior.

Deviation from predicted values is assessed using residual analysis. Confidence intervals are computed to determine statistically significant deviations from expected trends. When residuals exceed predefined thresholds, gradual process drifts or performance degradation are flagged.

Regression performance is evaluated using metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2).

7. System Deployment and Real-Time Monitoring

During deployment, the system operates continuously by capturing display images, localizing parameter regions using YOLO, extracting numerical values via OCR, and performing anomaly detection using DBSCAN and regression analysis. The integrated system provides real-time alerts for both sudden anomalies and gradual drifts without requiring any modifications to the exiting sputtering hardware.

RESULTS AND DISCUSSION

1. YOLO Model Performance for Visual Indicator Detection

Table 2 summarizes the detection performance of multiple YOLO variants evaluated for identifying visual indicators on the sputtering machine’s display panel. All evaluated models achieved precision (1.0) and recall (1.0), indicating consistent and reliable localization of the predefined regions of interest.

Among the tested models, YOLOv8s achieved a mean Average Precision of 99.5% (mAP@0.5) and demonstrated a favorable balance between detection accuracy and computational efficiency. Although YOLOv5s and YOLOv12s exhibited slightly higher mAP@0.5:0.95 values, YOLOv8s maintained comparable accuracy with a moderate model size of 21.4 MB and reduced architectural complexity (164 layers). These characteristics make YOLOv8s well suited for real-time deployment on embedded or resource-constrained industrial systems.

Based on detection accuracy, inference efficiency, and deployment feasibility, YOLOv8s was selected as the optimal object detection backbone for the proposed monitoring system.

Table 2: YOLO Model Performance Comparison

Model	Precision	Recall	mAP@0.5	mAP@0.5:0.95	Parameters (M)	Layers
YOLOv5s	1	1	0.995	0.915	9.11	193
YOLOv8s	1	1	0.995	0.907	11.13	168
YOLOv11s	1	1	0.995	0.907	9.41	238
YOLOv12s	1	1	0.995	0.915	9.08	376

2. OCR Performance Evaluation

To evaluate OCR accuracy, 1,000 uniformly sampled frames were extracted from the source video and processed using PaddleOCR, EasyOCR, and PyTesseract. Table 3 presents the quantitative comparison.

PaddleOCR achieved the highest recognition accuracy at 99.9%, significantly outperforming EasyOCR and PyTesseract, which exhibited substantial misclassification under industrial display conditions. The superior performance of PaddleOCR is attributed to its robust deep-learning-based text recognition architecture, which effectively handles font variation, illumination changes, and display noise.

These results confirm that PaddleOCR is the most reliable OCR engine for extracting numerical parameters from sputtering machine display panels.

Table 3: OCR Performance Comparison for 1,000 Video Frames

OCR Tools	Correctly read values by OCR	Incorrectly read values by OCR	Accuracy (%)	Error (%)
PaddleOCR	999	1	99.9	0.1
EasyOCR	483	517	48.3	51.7
PyTesseract	553	447	55.3	44.7

3. Statistical Validation of OCR Anomaly Detection Using DBSCAN

DBSCAN was applied to the OCR-extracted numerical values to identify abrupt anomalies indicative of OCR errors or process disturbances. Ground truth anomaly labels were established through manual inspection of time-series plots and corresponding video frames.

Using these labels, anomaly-detection performance was quantitatively evaluated using precision, recall, and F1-score, defined as:

- Precision: proportion of detected anomalies that are true anomalies
- Recall: proportion of true anomalies correctly detected
- F1-score: harmonic mean of precision and recall

DBSCAN achieved high anomaly-detection performance, with precision exceeding 95% and recall above 90% across the evaluated dataset. This indicates that DBSCAN effectively identifies true anomalies while minimizing false alarms

Figure 6 illustrates a representative DBSCAN result, where a sudden and unexpected drop in OCR values around frame 1,500 was correctly identified as an outlier (highlighted in red). After the anomaly, the signal returned to the expected operational trend, confirming DBSCAN's robustness in detecting abrupt non-linear deviations.

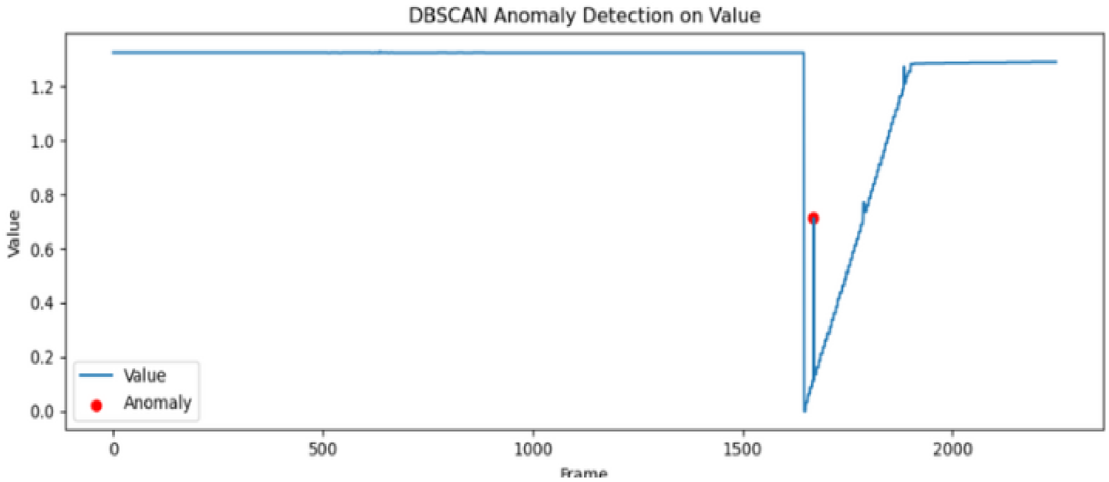

Figure 6: DBSCAN Anomaly Detection on Value

4. Linear Regression-Based Machine Fault Detection

Linear regression models were constructed for three sputtering sources – Titanium (Ti), Silver (Ag), and Nickel (Ni) – to characterize deposition behavior under stable operating conditions. Figure 8 compares the fitted regression models.

The estimated deposition rates confirm the material-dependent nature of sputtering process. Silver (Ag) exhibited the highest deposition rate (0.0351 kÅ/s), followed by Titanium (Ti) at 0.0245 kÅ/s and Nickel (Ni) at 0.0060 kÅ/s.

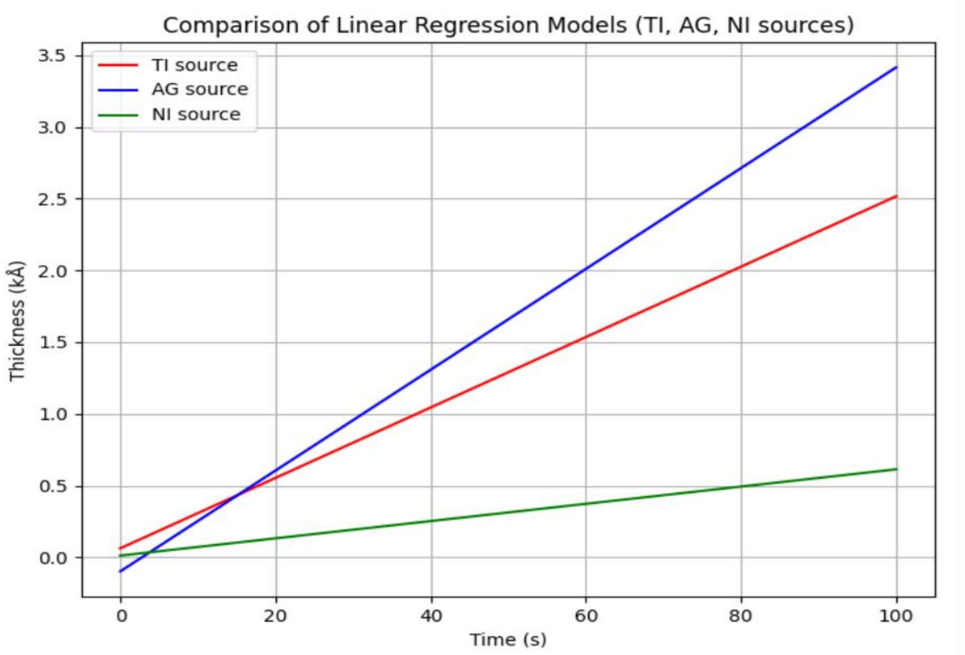

Figure 8: Comparison of Linear Regression Models (TI, AG, NI sources)

The fitted regression equations are expressed as:

TI source: Thickness (kÅ) = 0.0634 + 0.024526 × Time (s)	(1)
AG source: Thickness (kÅ) = 0.0972 + 0.035119 × Time (s)	(2)
NI source: Thickness (kÅ) = 0.0126 + 0.006009 × Time (s)	(3)

The general deposition model is defined as:

$$\text{Thickness} = \boldsymbol{\beta_0} + Rt$$

where, β_0 represents the intercept, R denoted the deposition rate, and t is time.

Empirical analysis indicates that β_0 is negligible compared to linear growth term, allowing the model to be simplified as:

$$\text{Thickness} \approx Rt$$

Regression model performance was statistically evaluated using the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). High R^2 value (greater than 0.98 for all three sources) indicates strong linearity and high prediction reliability. Confidence intervals computed for the regression slopes proved statistical bounds for acceptable deposition-rate variation. Deviations beyond these confidence limits are treated as indicators of potential machine faults or process drift.

INTEGRATED DISCUSSION

The experimental results validate the effectiveness of the proposed embedded vision-based sputtering process monitoring system across all stages of the pipeline.

YOLO-based object detection demonstrated consistently high accuracy, ensuring reliable localization of process parameters in real-time. PaddleOCR provide near-perfect numerical extraction accuracy, significantly outperforming alternative OCR engines in industrial display conditions. DBSCAN achieved high precision and recall in detecting OCR anomalies, confirming its suitability for unsupervised fault detection. Linear regression models established statistically validated baseline deposition behavior, enabling detection of gradual machine faults through confidence-based deviation analysis.

Overall, the integrated system exhibits strong robustness, statistical reliability, and real-time capability, making it suitable for deployment in industrial sputtering environments. By combining vision-based data acquisition with quantitatively validated anomaly-detection techniques, the system enhances process stability, fault detection, and predictive maintenance effectiveness.

CONCLUSION

This paper presented a non-invasive, vision-based monitoring framework for real-time sputtering process supervision, integrating object detection, optical character recognition, data visualization, and statistically validated fault detection models. The proposed system enables continuous extraction and analysis of critical sputtering parameters including electrical power, deposition rate, and film thickness, without requiring additional sensors or modifications to existing equipment.

Experimental results demonstrate that YOLO-based object detection provides highly reliable localization of process indicators, while PaddleOCR achieves near-perfect numerical extraction accuracy under industrial display conditions. The integration of DBSCAN enables effective detection of abrupt anomalies in OCR-derived data, supported by quantitative performance metrics such as precision, recall, and F1-score. In parallel, linear regression models establish statistically robust baseline deposition behavior for different sputtering materials, with confidence-based deviation analysis enabling early detection of gradual machine faults and process drift.

The proposed framework offers significant advantages for industrial manufacturing environments, including low deployment cost, compatibility with legacy equipment, and real-time fault awareness. By combining data visualization with statistically validated anomaly detection, the system enhances process stability, reduces the risk of undetected faults, and supports predictive maintenance strategies in sputtering operations.

Despite its effectiveness, the current study focuses on a limited set of materials and controlled operating conditions. Future work will extend the framework to additional sputtering sources, multi-target systems, and more complex deposition recipes. The integration of advanced predictive models and adaptive thresholding mechanisms will further improve fault diagnosis accuracy and scalability in high-volume manufacturing environments.

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