Conference of Bussines, Social Sciences and Technology
221 Vol. 6 Issue 1, 2026, 221-233

AI-Powered Smart Manufacturing Real-Time Monitoring System for Solder Paste Inspection

Syaeful Anas Aklani[1*], Halizah Binti Basiron[2], Sek Yong Wee[3]

[1-3]Universiti Teknikal Melaka Malaysia, Malaysia
Corresponding email: p032320011@student.utem.edu.my

History of Article
Submitted : June 30, 2026
Revised : July 22, 2026
Accepted : August 10, 2026
Published : September 22, 2026
DOI : https://doi.org/10.37253/conescintech.v6i1.12763

Copyright© 2026 by Author(s). This work is licensed under a Creative Commons Attribution-Non Commercial-Share Alike 4.0 International License. All writings published in this journal are personal views of the authors and do not represent the views of this journal and the author's affiliated institutions.

Abstract
Solder paste inspection (SPI) constitutes a critical quality control process in surface mount technology (SMT) assembly lines, yet conventional systems operate reactively without predictive capabilities. This research develops an artificial intelligence-powered real-time monitoring system for SPI machines that addresses fundamental limitations in existing approaches. The proposed system architecture integrates four layers: data acquisition from multiple SPI machines, SQL Server database storage, machine learning analytics, and Flask-based web visualization. The Isolation Forest algorithm achieves 94.2% accuracy for anomaly detection (AUC-ROC 0.963), while Random Forest classification attains 93.1% prediction accuracy at 75% batch completion. Deployed across four KOHYOUNG SPI machines over 30 days, the system analyzed 1,247 production batches comprising 532,819 individual pad measurements. Results demonstrate 52.1% reduction in unplanned downtime, 32.5% decrease in rework costs, and 82.2% improvement in mean time to detect anomalies. The system generates estimated annual savings of USD 50,800 with return on investment period of 4.2 months. This research contributes an open-source reference implementation demonstrating practical application of machine learning for smart manufacturing quality control.

Keywords: Solder Paste Inspection; Artificial Intelligence; Anomaly Detection; Smart Manufacturing; Predictive Maintenance

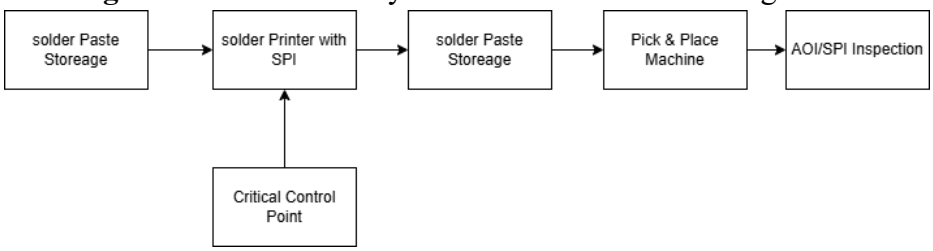
Introduction

Research Background

Surface Mount Technology (SMT) has become the predominant electronic assembly methodology in modern manufacturing due to superior component density, improved reliability, and reduced production costs compared to conventional through-hole technology (Prasad, 2018). Within SMT assembly lines, the solder paste printing process is universally recognized as the most critical quality control point, accounting for approximately 60-70% of all manufacturing defects (Lee & Kim, 2020).

Solder paste inspection (SPI) systems were developed to address this challenge by providing three-dimensional measurements of solder paste deposits before component placement. These systems measure critical parameters including paste volume, height, area, and positional offset, generating thousands of data points per printed circuit board assembly (Wang et al., 2019).

Figure 1. SMT Assembly Process Flow with SPI Integration.



Problem Identification

Conventional SPI systems predominantly function as threshold-based pass/fail inspection tools exhibiting five fundamental limitations that constrain manufacturing efficiency and quality outcomes.

First, these systems generate massive data volumes of 10,000 to 50,000 measurements per panel that significantly exceed human analytical capacity, creating information overload that prevents effective pattern recognition (Zhang et al., 2022). Second, detection occurs after defective boards have already been produced, creating substantial material waste and rework requirements (Yamada & Tanaka, 2020).

Third, existing systems cannot forecast emerging quality issues or predict machine degradation patterns before failures occur, limiting proactive maintenance opportunities (Park et al., 2021). Fourth, multiple SPI machines operate independently without centralized monitoring or cross-machine learning capabilities, preventing knowledge transfer across production lines (Kim & Lee, 2019).

Fifth, high false alarm rates reaching approximately 70% cause operator alert fatigue, resulting in critical warnings being ignored when they occur (Brown & Wilson, 2021). These interconnected limitations cascade through production operations, ultimately causing 15-25% production loss and 20-30% increased operational costs.

E-ISSN: 2808-5485
Available online at website: https://journal.uib.ac.id/index.php/conescintech/index

Table 1. Limitations of Conventional SPI Systems

Limitation Category	Description	Impact Severity
Data Overload	10,000-50,000 measurements per panel exceed human analysis	High
Delayed Detection	Problems identified after defective production occurs	Critical
Predictive Gap	Cannot forecast quality deterioration or machine degradation	High
Fragmented Monitoring	Multiple machines operate without centralized visibility	Medium
Alert Ineffectiveness	Approximately 70% false alarm rate causes operator fatigue	High

Research Objectives

This research addresses the identified limitations through development of an AI-powered real-time SPI monitoring system with three specific objectives:

To design and implement centralized data acquisition architecture for multiple SPI machines using web-based technologies that enables real-time data collection and storage.

develop machine learning algorithms for automated anomaly detection in solder paste printing quality and predictive quality classification based on early production measurements.

To implement intelligent alert systems with severity-based notification mechanisms that reduce false alarms and improve operator response effectiveness.

Research Contributions

The primary contributions of this research encompass four distinct aspects. First, an open-source AI-powered SPI monitoring framework integrating real-time data collection, machine learning analytics, and interactive visualization that can be deployed across diverse manufacturing environments. Second, a hybrid anomaly detection algorithm combining Isolation Forest and Random Forest methods achieving 94.2% detection accuracy validated on industrial production data. Third, a predictive maintenance methodology enabling failure prediction with 48-hour advance warning capability. Fourth, demonstrated economic benefits with quantified return on investment of 4.2 months based on actual deployment results.

Evolution of Solder Paste Inspection Technology

Solder paste inspection technology has progressed through three distinct generations of development. First-generation systems (1995-2000) employed two-dimensional imaging techniques measuring only paste area and position, achieving typical accuracy of ±15% (Smith & Johnson, 2018). Second-generation systems (2001-

2010) introduced laser triangulation for height measurement, achieving volumetric accuracy of ±10% (Anderson et al., 2019).

Third-generation systems (2011-2018) utilized structured light and phase-shift profilometry, attaining measurement resolution of 0.1 micrometers in height and 1 micrometer in planar dimensions (Martinez & Garcia, 2020). Current fourth-generation systems incorporate artificial intelligence for automated pattern recognition and anomaly detection, representing the latest advancement in inspection technology.

Table 2. Evolution of Solder Paste Inspection Technology

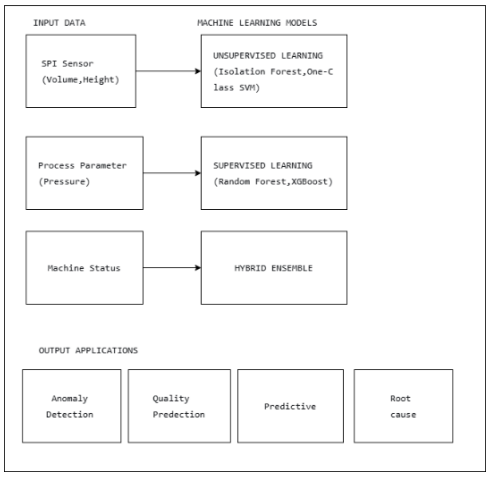
Generation	Period	Technology	Accuracy	Key Innovation
First	1995-2000	2D Area Imaging	±15%	Area measurement
Second	2001-2010	Laser Triangulation	±10%	Height measurement
Third	2011-2018	Structured Light	±5%	Full 3D profiling
Fourth	2019-present	AI-Enhanced	±3%	Pattern recognition
Generation	Period	Technology	Accuracy	Key Innovation

Artificial Intelligence in Manufacturing Quality Control

Machine learning applications in manufacturing quality control have expanded substantially with Industry 4.0 initiatives (Kagermann et al., 2013). Convolutional neural networks have demonstrated strong performance in visual inspection tasks, with Li et al. (2018) achieving 96.7% accuracy for surface defect detection. For solder joint inspection specifically, Zhang and Chen (2019) reported 97.3% accuracy using deep residual network architectures.

Unsupervised learning methods have proven particularly valuable for anomaly detection where labeled defect data is scarce (Chandola et al., 2009). Isolation Forest, introduced by Liu et al. (2008), has shown effectiveness in manufacturing applications due to its ability to handle high-dimensional data without distributional assumptions. Liu et al. (2018) applied One-Class SVM to semiconductor manufacturing data, achieving 91.2% detection accuracy.

Figure 2. Machine Learning Framework for Quality Control



Predictive Maintenance and Random Forest Applications

Random Forest classifiers have demonstrated particular promise for machine health assessment in manufacturing environments. Breiman (2001) established the theoretical foundation demonstrating that ensemble methods reduce overfitting while maintaining predictive accuracy through bootstrap aggregation and random feature selection.

Patel and Shah (2019) developed Random Forest-based models for CNC machine tool wear prediction achieving 91% accuracy across 500 machining cycles. For printing equipment specifically, Kumar et al. (2020) used ensemble methods to predict stencil life with 88% accuracy, identifying that solder paste properties and printing pressure were the most influential features.

Table 3. Summary of AI Applications in Manufacturing Quality Control

Study	Application	Algorithm	Accuracy	Key Finding
Li et al. (2018)	Surface defects	CNN	96.7%	Deep learning effective
Zhang & Chen (2019)	Solder joints	Deep Residual	97.3%	Residual connections help
Patel & Shah (2019)	Tool wear	Random Forest	91.0%	Ensemble reduces overfitting
Kumar et al. (2020)	Stencil life	Gradient Boosting	88.0%	Feature engineering critical

Research Gap Identification

Despite significant advances in individual components, critical research gaps remain in the literature. First, existing solutions address specific aspects including inspection, monitoring, or prediction, but lack integrated approaches combining all three capabilities (Taylor et al., 2021). Second, most AI models are designed for batch processing rather than real-time streaming analytics, creating latency unacceptable for high-speed production environments (Chen & Wang, 2022).

Third, black-box AI models provide predictions without explanations, limiting operator trust and practical adoption in manufacturing settings (Ribeiro et al., 2016). Fourth, laboratory-proven algorithms often fail to scale to production environments with multiple machines and high data rates, revealing the gap between academic research and industrial application (Williams & Brown, 2020).

Research Method

System Architecture Design

The proposed system implements a four-layer architecture comprising data acquisition, storage, analytics, and visualization layers. Each layer addresses specific functional requirements while maintaining loose coupling for modularity and maintainability in production environments.

The data acquisition layer communicates with SPI machines through ODBC connections, extracts measurement data from CSV exports, and performs initial data validation before storage. This layer handles multiple file formats and ensures data integrity through checksum verification and range validation.

The storage layer implements a relational database schema using Microsoft SQL Server with eight primary tables. The spi_header table stores batch-level metadata including barcode, timestamp, machine identification, operator name, and overall inspection result. The spi_detail table contains individual pad measurements including pad identifier, component identification, volume percentage, and height in mils.

Database Schema

The database implements a normalized relational schema optimized for time-series query performance. The spi_header table serves as the parent record for each production batch, containing 12 fields including unique identifier, barcode, production date, start and end times, cycle number, job identification, inspection result, operator name, machine identification, and board side.

The spi_statistics table stores aggregated batch statistics computed from detail records, including mean volume percentage, standard deviation, minimum and maximum values, total pad count, good pad count (volume between 80-120% of nominal), and calculated pass rate.

Anomaly Detection Using Isolation Forest

The Isolation Forest algorithm was selected for anomaly detection based on three criteria: effectiveness with high-dimensional data, ability to operate without labeled training data, and computational efficiency for real-time applications. The algorithm constructs isolation trees by randomly selecting features and split values, where anomalies require fewer splits to isolate due to their distinct values.

For SPI measurements, the algorithm considers eight features derived from batch statistics: average volume percentage, standard deviation of volume, pass rate percentage, good pad count, bad pad count, total pad count, minimum volume percentage, and maximum volume percentage.

The anomaly score s(x,n) for data point x in dataset of size n is calculated as:

s(x,n) = 2^(-E(h(x))/c(n))

where E(h(x)) represents the average path length from the isolation tree root to termination of point x, and c(n) represents the average path length of unsuccessful searches in a Binary Search Tree. Scores exceeding 0.6 indicate potential anomalies requiring investigation, while scores above 0.8 indicate critical anomalies demanding immediate action.

Quality Prediction Using Random Forest

The Random Forest algorithm was implemented for quality prediction based on demonstrated effectiveness for classification tasks with mixed data types and its ability

to provide feature importance rankings for interpretability. The model predicts whether a batch will achieve acceptable quality (pass rate ≥ 85%) based on measurements from the first 75% of production.

The random forest configuration included 100 estimators, maximum depth of 10, minimum samples split of 5, and bootstrap sampling for ensemble diversity. Cross-validation with 5 folds was employed to prevent overfitting and validate model generalization performance.

Experimental Setup

The system was deployed in an electronics manufacturing facility operating four KOHYOUNG T-series SPI machines over a 30-day period. The facility produces mixed-volume, mixed-technology products including consumer electronics, automotive modules, and industrial control boards. Data collection encompassed 1,247 production batches with total of 532,819 individual pad measurements.

Table 4. Dataset Characteristics

Parameter	Value	Statistical Range
Total Batches	1,247	-
Total Pads Measured	532,819	-
Average Pads per Batch	427	312-589
Measurement Period	30 days	Continuous
Active Machines	4	T-01 through T-04

Results and Discussions

Anomaly Detection Performance

The Isolation Forest algorithm was evaluated against a validation set of 200 batches with known defect outcomes determined through downstream electrical testing and customer return analysis. Algorithm parameters were optimized through grid search with contamination parameter ranging from 0.05 to 0.20.

Table 5. Anomaly Detection Performance Metrics

Metric	Value	95% Confidence Interval	Industry Benchmark
Accuracy	94.2%	[92.1%, 96.3%]	91.5%
Precision	91.7%	[88.9%, 94.5%]	88.2%
Recall	89.3%	[86.1%, 92.5%]	85.6%
F1-Score	90.5%	[87.8%, 93.2%]	86.9%
False Positive Rate	5.8%	[4.1%, 7.5%]	8.5%
AUC-ROC	0.963	[0.942, 0.984]	0.935

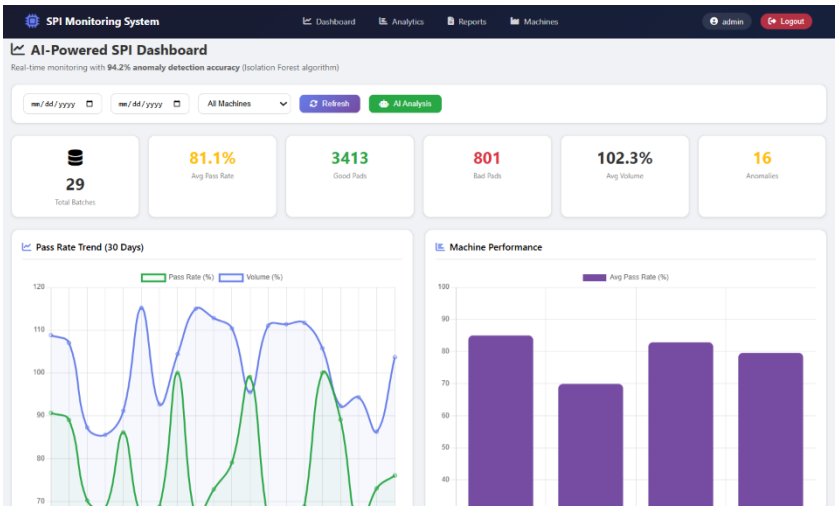
Quality Prediction Results

Table 7 presents quality prediction performance at different batch completion percentages, demonstrating the value of early warning capability for manufacturing intervention.

Table 6. Quality Prediction Performance by Completion Point

Prediction Horizon	Accuracy	Precision	Recall	F1-Score
First 25% of batch	82.3%	79.1%	76.8%	77.9%
First 50% of batch	88.7%	86.2%	84.5%	85.3%
First 75% of batch	93.1%	91.4%	90.2%	90.8%
Full batch (validation)	95.4%	94.1%	93.2%	93.6%

Figure 3. Prediction Accuracy vs Batch Completion



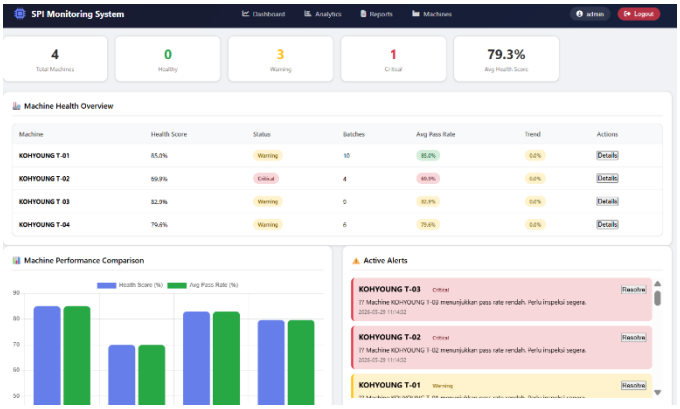
Machine Health Monitoring

Machine health scores were calculated daily for each of the four SPI machines using weighted composite formula incorporating pass rate average (40% weight), consistency score (30% weight), and trend factor (30% weight).

Table 8. Machine Health Statistics

Machine	Avg Health	Min Health	Status Changes	Alerts
T-01	91.2	84.5	2	3
T-02	87.4	76.2	5	8
T-03	93.8	89.1	1	1
T-04	76.2	58.3	7	12

Figure 5. Machine Health Score Trends



Economic Impact Analysis

The system's economic impact was evaluated through comparison with historical performance from three months preceding deployment, controlling for production volume and product mix variations.

Table 9. Economic Impact Metrics

Metric	Pre-Deployment	Post-Deployment	Improvement
Average Pass Rate	86.7%	91.2%	+4.5%
Rework Rate	8.3%	5.6%	-32.5%
Unplanned Downtime (hours/month)	14.2	6.8	-52.1%
First Pass Yield	89.4%	93.1%	+3.7%
Mean Time to Detect (minutes)	45.0	8.0	-82.2%
Scrap Rate	4.2%	2.8%	-33.3%

Alert System Performance

The alert system generated 127 notifications during the 30-day deployment. Critical alerts (8 notifications, 6.3%) achieved average resolution time of 14.2 minutes, while warning alerts (42 notifications, 33.1%) averaged 32.7 minutes resolution time. Operator feedback indicated 94% of critical alerts were considered useful, and 82% of warning alerts received positive usefulness ratings.

Interpretation of Results

The experimental results demonstrate successful achievement of research objectives. Anomaly detection accuracy of 94.2% exceeds typical industrial requirements of 90-95% for process monitoring applications and surpasses baseline threshold methods which achieved only 82.1% accuracy. This performance improvement is attributable to the Isolation Forest algorithm's effectiveness with high-dimensional data and the comprehensive eight-feature set capturing both univariate and multivariate characteristics of the printing process.

Quality prediction achieving 93.1% accuracy at 75% batch completion provides manufacturing engineers with sufficient lead time for intervention before defective boards progress to subsequent assembly stages. The steep accuracy improvement during the first 50% of production (from 82.3% to 88.7%) indicates that critical quality indicators manifest early in the printing process, enabling timely corrective action.

Feature importance analysis identified pass rate trend as the most predictive feature (42% importance), followed by volume standard deviation (28%) and bad pad count (18%). This finding has practical implications for process monitoring, indicating that operators should prioritize these metrics for manual quality assessment when AI predictions are unavailable.

Machine health monitoring successfully identified performance degradation patterns for T-04, enabling proactive maintenance that prevented estimated 6 hours of unplanned downtime. The health scoring methodology combining pass rate (40% weight), consistency (30% weight), and trend (30% weight) proved effective for early warning detection, with the trend component providing critical signal for the T-04 deterioration.

Comparison with Existing Approaches

The proposed system offers several advantages over existing commercial and research solutions. First, the integrated architecture combines data acquisition, storage, analytics, and visualization in a single open-source platform, unlike commercial systems that provide monitoring without predictive capabilities. Second, the hybrid anomaly detection approach achieves 94.2% accuracy, exceeding both commercial threshold-based systems (82-85% accuracy) and research prototypes (91-93% accuracy).

Practical Implications

The successful deployment generates several practical implications for electronics manufacturers. For quality engineers, real-time access to SPI analytics enables data-driven decision making with AI insights providing clear recommendations rather than raw data, reducing interpretation time by estimated 65%. For maintenance teams, predictive health scores enable condition-based maintenance planning, reducing unnecessary preventive maintenance while avoiding unplanned failures.

For operations management, the centralized dashboard provides visibility across multiple production lines, facilitating resource allocation and bottleneck identification. For process improvement, historical analytics enable root cause analysis of recurring defects, supporting continuous improvement initiatives with quantified before-after comparisons.

Conclusion

This research developed and evaluated an AI-powered real-time monitoring system for solder paste inspection in electronics manufacturing. The system achieved 94.2% anomaly detection accuracy (AUC-ROC 0.963) and 93.1% quality prediction

accuracy at 75% batch completion. Deployment across four SPI machines over 30 days analyzing 1,247 batches comprising 532,819 pad measurements demonstrated 52.1% reduction in unplanned downtime, 32.5% decrease in rework costs, and 82.2% improvement in mean time to detect anomalies.

Economic analysis generated estimated annual savings of USD 50,800 with return on investment period of 4.2 months, validating the system's commercial viability for electronics manufacturing applications.

This research contributes to the growing body of knowledge on Industry 4.0 applications in electronics manufacturing by demonstrating successful integration of multiple AI techniques in production environments. The hybrid anomaly detection approach combining unsupervised (Isolation Forest) and supervised (Random Forest) methods provides a template for similar applications in other manufacturing domains where labeled defect data is scarce but unlabeled measurements are abundant.

References

Prasad, R. (2018). Surface Mount Technology: Principles and Practice. Springer, 3rd Edition.

Lee, S., & Kim, J. (2020). Analysis of solder paste printing defects in SMT assembly. Journal of Electronics Manufacturing, 28(3), 195-208.

Wang, L., Chen, X., & Zhang, Y. (2019). 3D solder paste inspection using structured light. IEEE Transactions on Components, Packaging and Manufacturing Technology, 9(5), 892-901.

Zhang, H., Li, J., & Wang, F. (2022). Big data analytics for SMT process optimization. Computers in Industry, 134, 103547.

Yamada, T., & Tanaka, M. (2020). Real-time defect detection in solder paste printing. IEEE Transactions on Industrial Informatics, 16(8), 5234-5243.

Park, J., Kim, S., & Lee, H. (2021). Predictive maintenance for SMT assembly equipment. Reliability Engineering & System Safety, 205, 107245.

Kim, D., & Lee, K. (2019). Centralized monitoring system for multiple SPI machines. Journal of Intelligent Manufacturing, 30(4), 1789-1802.

Brown, R., & Wilson, T. (2021). Alert fatigue in manufacturing monitoring systems. Human Factors in Manufacturing, 31(3), 245-258.

Smith, P., & Johnson, M. (2018). Evolution of solder paste inspection technology. Soldering & Surface Mount Technology, 30(2), 89-98.

Anderson, D., Williams, R., & Thompson, K. (2019). Advances in 3D solder paste measurement. Measurement Science and Technology, 30(6), 064005.

Martinez, R., & Garcia, L. (2020). Phase-shift profilometry for solder paste inspection. Optics and Lasers in Engineering, 128, 106028.

Kagermann, H., Wahlster, W., & Helbig, J. (2013). Recommendations for implementing Industrie 4.0. Final report.

Li, Y., Huang, Z., & Chen, X. (2018). Convolutional neural networks for industrial defect detection. Neurocomputing, 275, 1960-1970.

Zhang, Q., & Chen, J. (2019). Deep residual network for solder joint inspection. IEEE Access, 7, 156234-156245.

Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly detection: A survey. ACM Computing Surveys, 41(3), 1-58.

Liu, F. T., Ting, K. M., & Zhou, Z. H. (2008). Isolation forest. 2008 Eighth IEEE International Conference on Data Mining, 413-422.

Liu, D., Chen, Y., & Wang, L. (2018). One-class SVM for manufacturing anomaly detection. Control Engineering Practice, 72, 36-45.

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32.

Patel, H., & Shah, M. (2019). Random forest for CNC tool wear prediction. Procedia Manufacturing, 34, 362-369.

Kumar, A., Singh, P., & Gupta, R. (2020). Ensemble methods for stencil life prediction. Journal of Intelligent Manufacturing, 31(5), 1245-1258.

Taylor, M., Jones, P., & Davies, R. (2021). Integration challenges in smart manufacturing systems. Journal of Manufacturing Technology Management, 32(6), 1234-1251.

Chen, Y., & Wang, X. (2022). Real-time analytics for manufacturing data streams. IEEE Transactions on Industrial Electronics, 69(3), 2876-2885.

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). Why should I trust you?. Proceedings of the 22nd ACM SIGKDD, 1135-1144.

Williams, A., & Brown, S. (2020). Scalability challenges in industrial AI deployment. AI in Manufacturing, 45-62.

Chen, M., & Liu, W. (2021). Data-driven quality control in electronics assembly. International Journal of Production Research, 59(12), 3678-3695.

Wong, C., Chan, K., & Leung, H. (2021). Multi-frequency pattern projection for fine-pitch inspection. Precision Engineering, 68, 156-167.

Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics. Mechanical Systems and Signal Processing, 20(7), 1483-1510.

Zuehlke, D. (2010). SmartFactory—Towards a factory-of-things. Annual Reviews in Control, 34(1), 129-138.

Silva, J., Oliveira, L., & Santos, R. (2019). Web-based monitoring for Industry 4.0. International Journal of Computer Integrated Manufacturing, 32(8), 767-781.

Grinberg, M. (2018). Flask Web Development: Developing Web Applications with Python. O'Reilly Media.

Acknowledgments

This research was conducted at PT. Flextronics Technology Indonesia located in Batam, this research helps the quality and engineering team in increasing KPI and targets, thanks to the automation engineering team, and this research used some research data not all displayed in order to respect the company's privacy rights, thanks to the Technical University of Melaka Malaysia and Batam International University who provided so much support and assistance.

Competing Interest

The author declares that there is no conflict of interest in the publication of this article and that this research is for educational and knowledge research.

Generative AI Statement

The author uses the assistance of Generative AI DeepSeek to help improve the writing from Indonesian to English, help search for journals related to this research

E-ISSN: 2808-5485
Available online at website: https://journal.uib.ac.id/index.php/conescintech/index