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AI- Based Failure Predction in PCBAs Using Automated Optical Inspection Data

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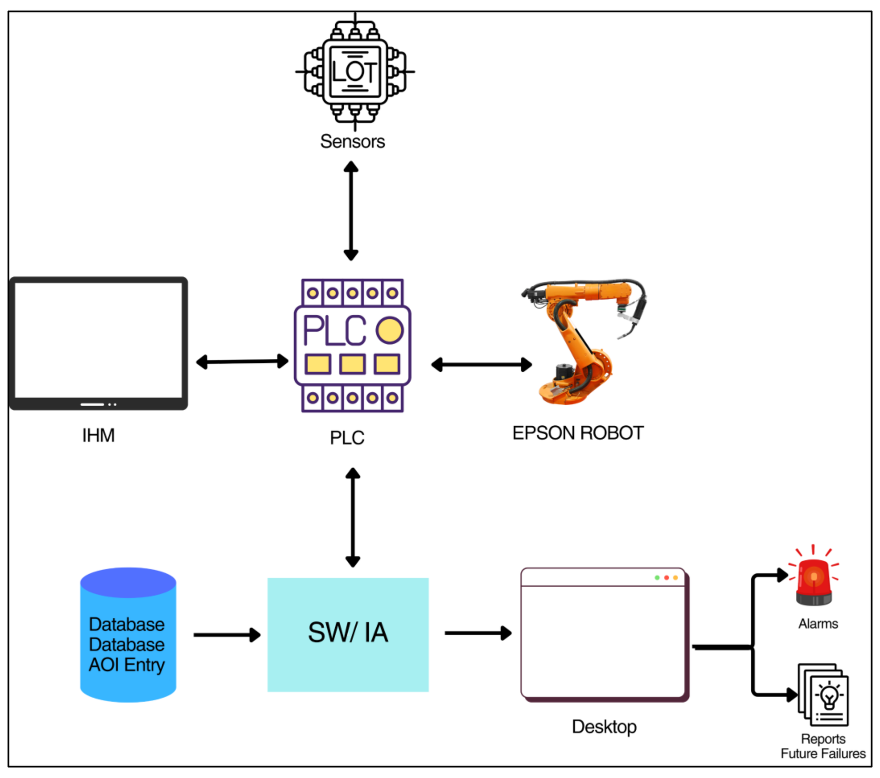
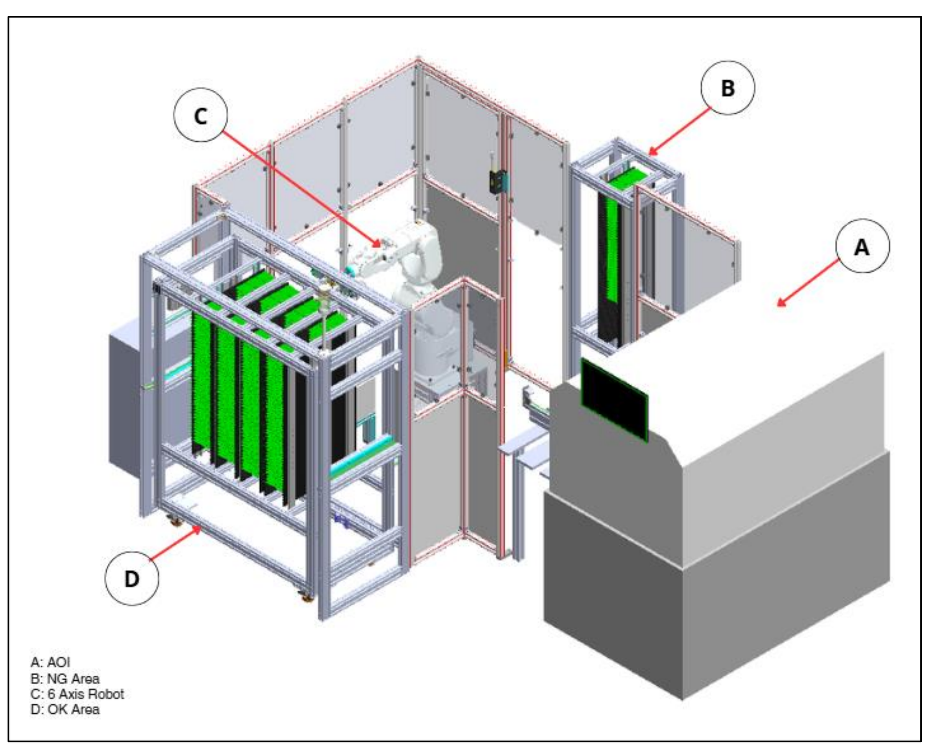
INTRODUCTION & AIM

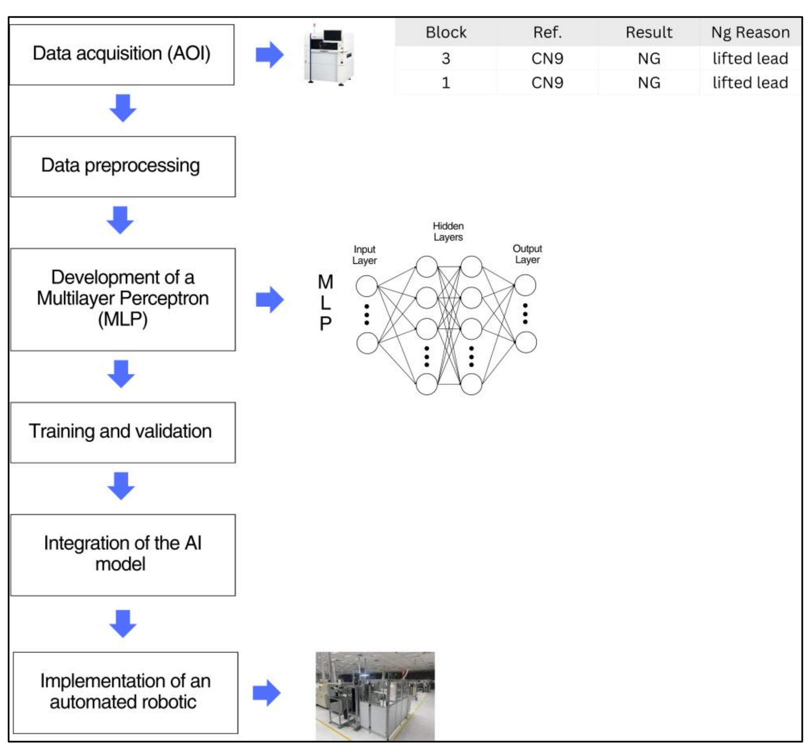
Automated Optical Inspection (AOI) systems in Surface Mount Technology (SMT) lines are widely used to detect defects such as component shifting and solder bridging. However, these systems operate mainly in a reactive manner, lacking predictive capabilities and root cause analysis [1][2]. In industrial environments, maintenance decisions are often based on empirical approaches, resulting in inefficiencies and limited process reliability [3].
Furthermore, the absence of models capable of correlating AOI inspection data with upstream process variables highlights a significant technical and scientific gap.
This work aims to develop and experimentally validate an artificial intelligence-based solution using a Multilayer Perceptron (MLP) to enable predictive failure analysis in SMT production lines [4]. The system correlates AOI defect data with real-time process variables acquired via Modbus TCP, including temperature, conveyor speed, component count, and solder paste volume, focusing on critical defects such as component shifting and bridging.
The proposed approach supports predictive maintenance, improves yield, and advances the system toward Industry 4.0 predictive maturity.



METHOD

The proposed methodology was structured into six main stages: (i) acquisition of AOI inspection data from a Yamaha YSi-V system combined with real-time process data collected via Modbus TCP; (ii) data preprocessing to handle noise, imbalance, and variability inherent to industrial environments [5]; (iii) development of a Multilayer Perceptron (MLP) model to identify correlations between process variables and defect occurrence [6]; (iv) training and validation using real production data; (v) integration of the AI model with industrial systems (AOI and MES) for real-time decision support; and (vi) implementation of an automated robotic cell with a 6-axis industrial robot for physical segregation of PCBAs based on model predictions.
The neural network was implemented using TensorFlow/Keras, with four input neurons corresponding to process variables, two hidden dense layers with ReLU activation and dropout regularization to mitigate overfitting, and a Softmax output layer to classify process conditions into three states: Normal, Shifting, and Bridging. The complete solution was validated in a real SMT production environment (Line S5).





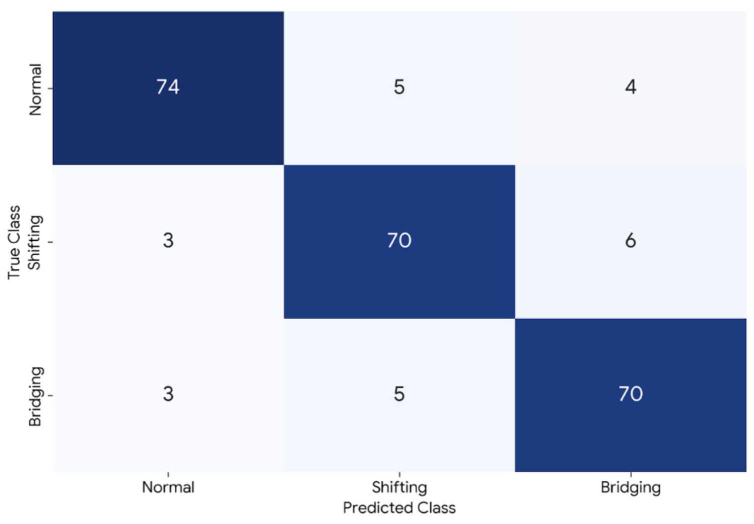
RESULTS & DISCUSSION

The developed model was trained on a dataset containing 1,200 samples, with 80% used for training and 20% for validation and testing. The model achieved an average accuracy of 89%, correctly classifying process conditions based exclusively on sensor data.
Beyond classification performance, the system demonstrated predictive capability by identifying process trends associated with defect generation, such as gradual increases in temperature leading to bridging defects before their physical occurrence in AOI inspection logs. This predictive behavior enables proactive intervention, reducing scrap and rework by allowing process adjustments before defects occur.
The integration of artificial intelligence with real-time industrial data proved effective in capturing complex relationships between process variables and defect formation, enhancing process reliability and overall operational efficiency.

Performance Metrics (N= 240 samples)

Class	Precision	Sensitivity	F1-Score	Qty Samples of the Class
Normal	0.92	0.89	0.91	83
Shifting	0.88	0.89	0.88	79
Bridging	0.88	0.9	0.89	78
Macro Average	0.89	0.89	0.89	240
Overall Accuracy	-	-	0.89	240

Confusion Matrix (Test: 240 samples)



CONCLUSION

The proposed solution successfully integrates Operational Technology (OT) with Information Technology (IT), creating an intelligent layer capable of identifying patterns not detectable through conventional analysis of industrial sensor data. The system demonstrated both classification and predictive capabilities, supporting decision-making and reducing process variability.
By enabling early detection of failure trends and supporting proactive maintenance strategies, the solution contributes to the advancement of SMT manufacturing toward Industry 4.0, reaching maturity level 5 (Predictive Capability) and reinforcing the role of artificial intelligence in smart manufacturing environments.

FUTURE WORK / REFERENCES

As an evolution of this work, we intend to:

- Expand the number of IoT sensors to monitor other variables (electrical current and vibration).

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