International Conference and Workshop on
Additive Manufacturing and Characterization
(ICAMC-2025, 09-11 Jan)

Unsupervised machine learning for anomaly detection in Wire-arc Additive Manufacturing

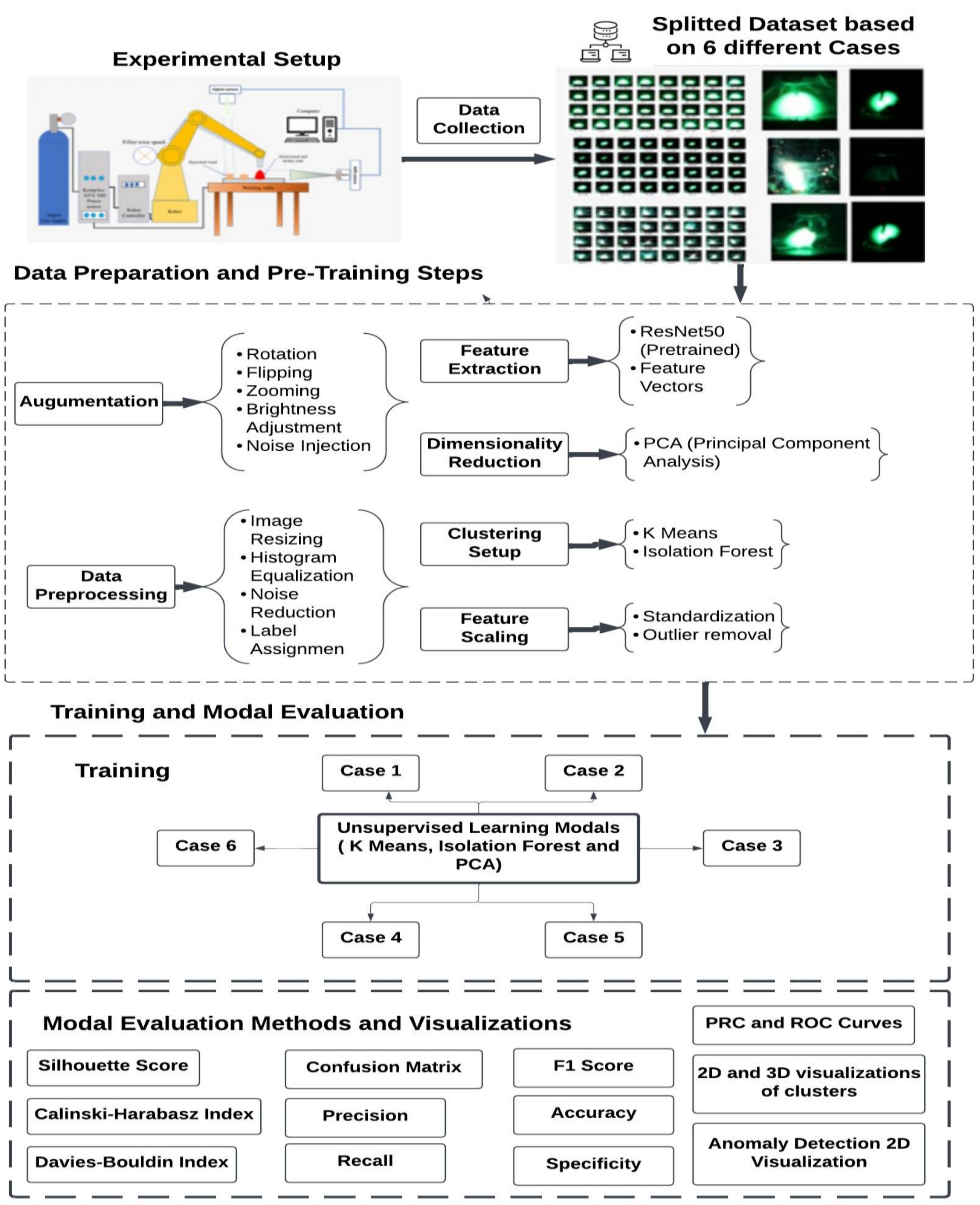
Priyanshu Bist[1] and Mukesh Chandra[2]
[1] Thapar Institute of Engineering and Technology, Patiala, Punjab and [2]BIT Sindri, Dhanbad, Jharkhand
mchandra018@gmail.com

Objective of the study

i. To apply unsupervised machine learning (UML) for anomaly detection in Wire-arc additive manufacturing (WAAM).
ii. To study the impact of the Image processing techniques on the ML modal performance.
iii. To test the developed UML pipeline and its deployment for real-time application in WAAM processes for improving the quality of fabricated part.

Research Methodology

(Experimental work, Data collection, and evaluation)



Conclusion and Innovation

- Case 1 with regular and irregular bead melt pool images performed well with excellent accuracy both with supervised and unsupervised machine learning models.
- Case 2 and Case 3 show optimal clustering performance with 3-4 clusters, achieving high accuracy and F1-scores, while performance degrades with more clusters.
- Case 4, Case 5, and Case 6 demonstrate moderate to low performance, highlighting the need for further model improvement, particularly due to challenges with precision, recall, and class imbalance.
- Effective results demonstrate the potential for automated detection of anomalies WAAM fabricated part for quality control in real-time.

Results & Discussion

- ResNet50 + PCA captured key features for anomaly detection.
- Histogram equalization enhanced image contrast and quality.
- Higher evaluation parameter values ensure reliable anomaly detection with slight room for improvement.
- Confusion matrix shows minimal misclassification.

Case 1: classification of regular and irregular beads

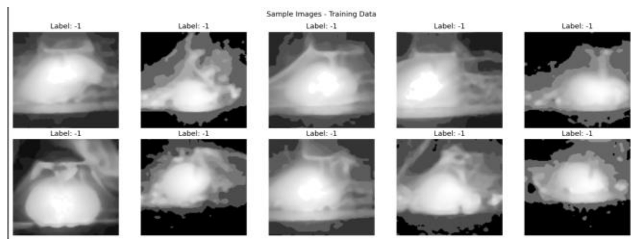


Fig.1: Sample of training dataset

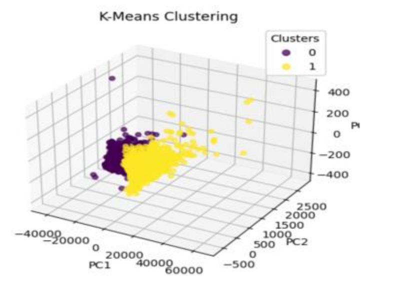


Fig.2: 3D visualization of clusters

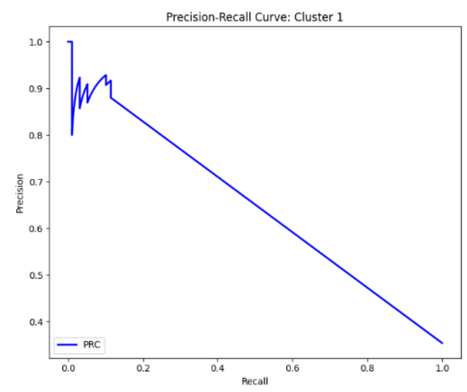


Fig.3: Precision-recall curve

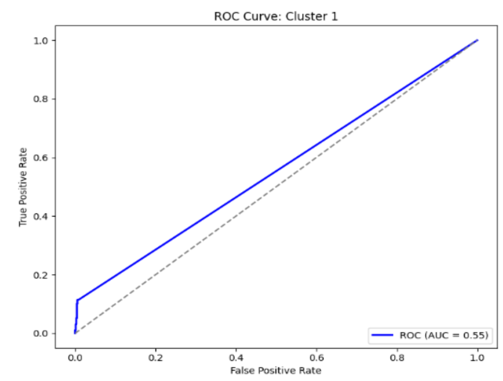


Fig.4 : ROC curve

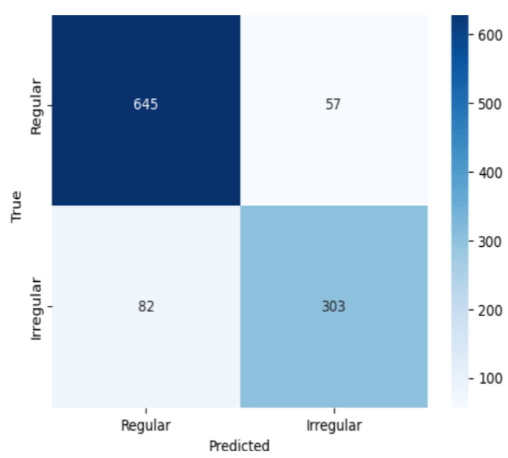


Fig.5: Confusion matrix

Metrics	Unsupervised	Supervised
Precision	0.8711	0.9763
Recall	0.8721	0.9826
F1 Score	0.8711	0.9794
AUC-ROC	0.55	0.92

Fig.6: Comparative Insights

Case 2, 3,4,5 & 6:

- **Case 2:** Optimal clustering occurred with **3-4 clusters**, achieving high accuracy **(93.99%)** and F1-score **(0.9681).** Performance degraded with more clusters, evidenced by declining silhouette, Calinski-Harabasz, and Davies-Bouldin scores.
- **Case 3:** Best performance with **3 clusters (66.18% accuracy, 0.7792 F1-score).** Performance decreased with more clusters. High precision but low recall/specificity suggested an imbalanced anomaly detection.
- **Case 4:** The model performs moderately with **51% accuracy**, but struggles with low precision for Regular beads **(0.41)** and moderate recall for Spatter) **(0.53).**
- **Case 5:** Clustering results show poor separation (silhouette score 0.40) with high precision **(0.79)** but very low recall **(0.15)**, leading to low F1 score **(0.26).**
- **Case 6:** The model shows balanced but low performance (**47% accuracy, F1 score 0.47**) with similar precision and recall for both classes.

References

1. Chandra, Mukesh, Sonu Rajak, and Vimal KEK. "Deep learning-based framework for the observation of real-time melt pool and detection of anomaly in wire-arc additive manufacturing." Materials and Manufacturing Processes 39.6 (2024): 761-777.
2. Song, Hao, et al. "A two-stage unsupervised approach for surface anomaly detection in wire and arc additive manufacturing." *Computers in Industry* 151 (2023): 103994.
3. Taherkhani, K., C. Eischer, and E. Toyserkani. "An unsupervised machine learning algorithm for in-situ defect-detection in laser powder-bed fusion. J Manuf Process 81: 476–489." 2022,