Leveraging Deep Learning Models for Thermal Anomaly Detection in Robot-Assisted Manufacturing

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BACKGROUND

- Robot-assisted manufacturing systems are production environments where robots and intelligent monitoring systems support human operators by performing tasks, analyzing process data, and detecting abnormalities to improve manufacturing reliability.
- In additive manufacturing (3D printing), a layer-by-layer fabrication process, thermal image anomaly detection analyzes heat-based images of the build process to identify abnormal patterns.

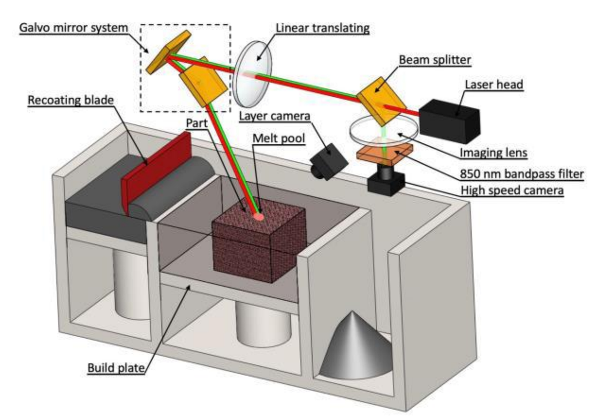

Fig 1. Additive manufacturing process

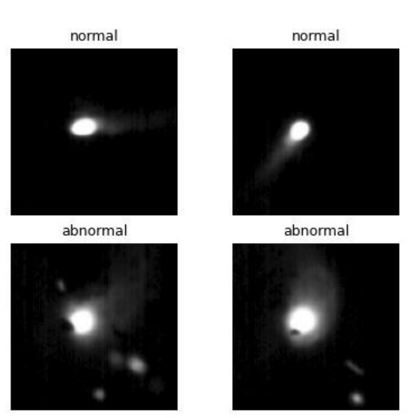

Fig 2. Normal vs. Abnormal

- Abnormal behavior refers to deviations in thermal image patterns, such as inconsistent brightness or scattered heat intensity, that differ from stable conditions and may indicate defects or process instability.
- Undetected thermal anomalies can lead to defective parts, structural weaknesses, and costly rework.
- Early detection enables corrective intervention before defects propagate, reducing material waste and improving production efficiency and reliability.

INTRODUCTION

- In additive manufacturing (3D printing), thermal anomaly detection uses deep learning models to identify abnormal heat patterns linked to defects or process instability.
- These models include supervised approaches trained on labeled data and unsupervised approaches that learn patterns from unlabeled data.
- Supervised models achieve high accuracy when labeled defect data is available.
- However, in real industrial environments, defect data is inherently rare, leading to class imbalance and limited abnormal samples. As a result, unsupervised methods are often preferred when anomalies are scarce or not fully characterized.
- Although supervised and unsupervised methods are well studied independently, fewer works directly compare their complementary strengths that balance detection accuracy with limited labeled data constraints.
- This study compares supervised and unsupervised deep learning models for thermal anomaly detection, analyzing the tradeoff between detection performance and labeled data dependence to inform the design of robust anomaly detection frameworks for robot-assisted additive manufacturing.

METHODS

- The study focused on a labeled grayscale thermal image dataset representing process states in a robot-assisted additive manufacturing system, consisting of 600 normal and 600 abnormal images.
- The dataset was preprocessed through resizing, normalization, and stratified partitioning into training and validation subsets using an 80:20 split to ensure consistent and unbiased evaluation.
- Two supervised models (Custom CNN, EfficientNetV2) and two unsupervised models (Convolutional Autoencoder and CAE + Isolation Forest) were developed to detect abnormal manufacturing behavior.
- All models were trained for 10 epochs (the number of times the model goes through the entire training dataset) to ensure sufficient convergence (the model's learning stabilizes) while limiting overfitting (memorizing the training data instead of generalizing).
- Model performance was evaluated using accuracy, confusion matrices, ROC curves, and AUC scores.

RESULTS

Comparative Model Performance

Learning Approach	Model	Accuracy (%)	AUC (area under the curve)
Supervised	Convolutional Neural Network (CNN)	96%	0.999
Supervised	EfficientNetV2	42%	0.523
Unsupervised	Convolutional Autoencoder	64%	0.669
Unsupervised	Convolutional Autoencoder + Isolation forest	67%	0.844

Detailed Performance of Best-Performing Model (CNN)

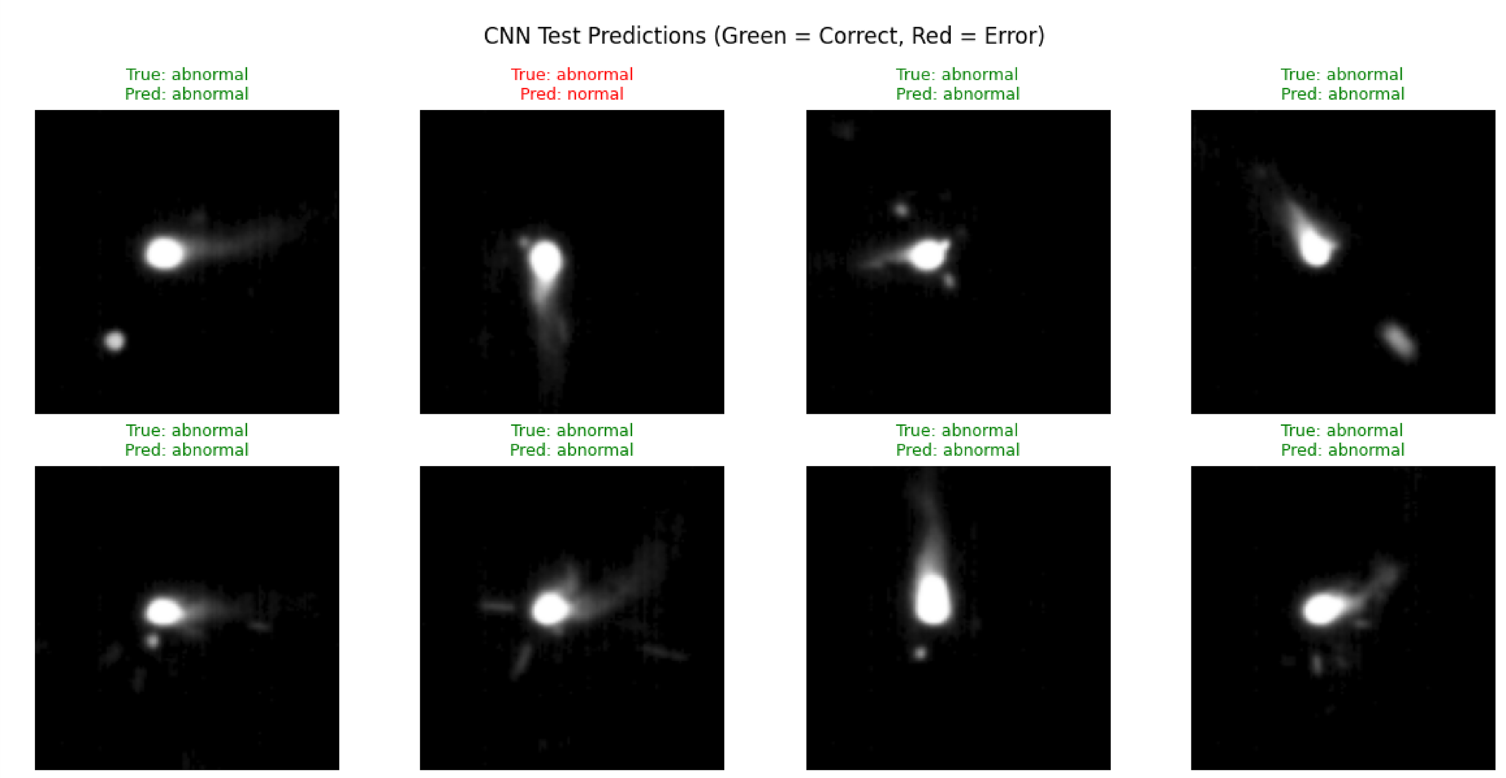

Fig 3. CNN Test Predictions

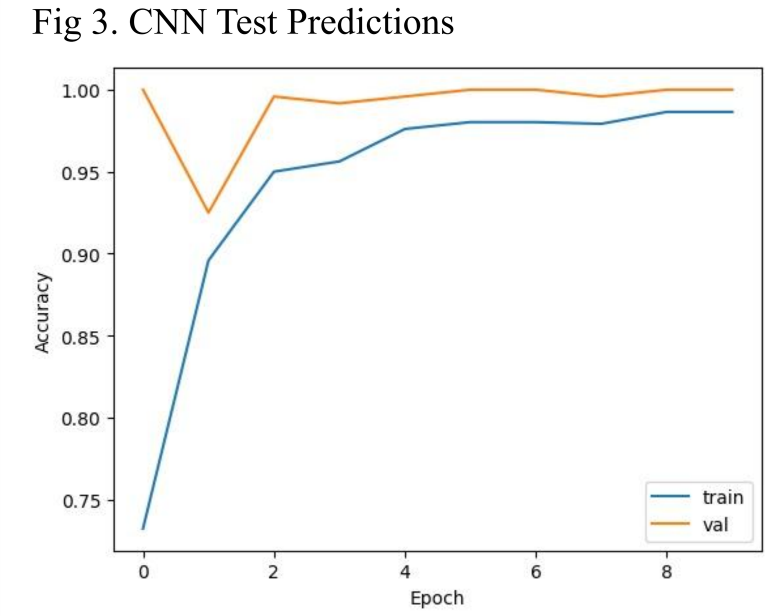

Fig 4. Training & Validation Accuracy for CNN

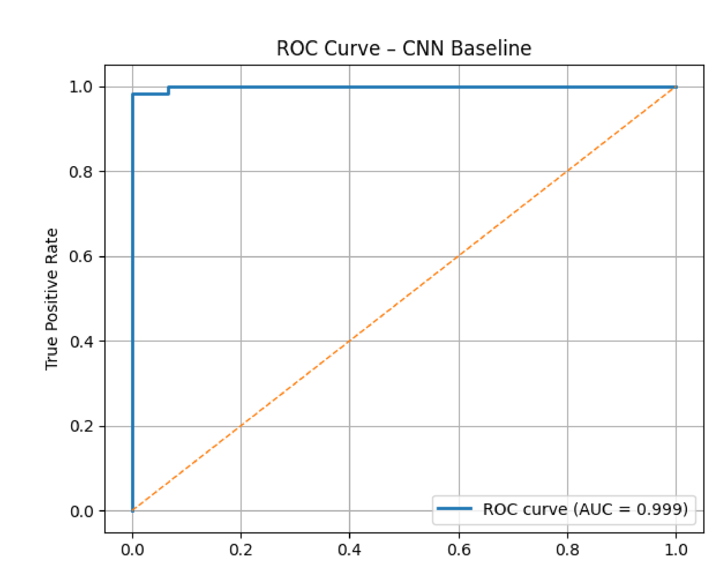

Fig 5. ROC Curve for CNN Model

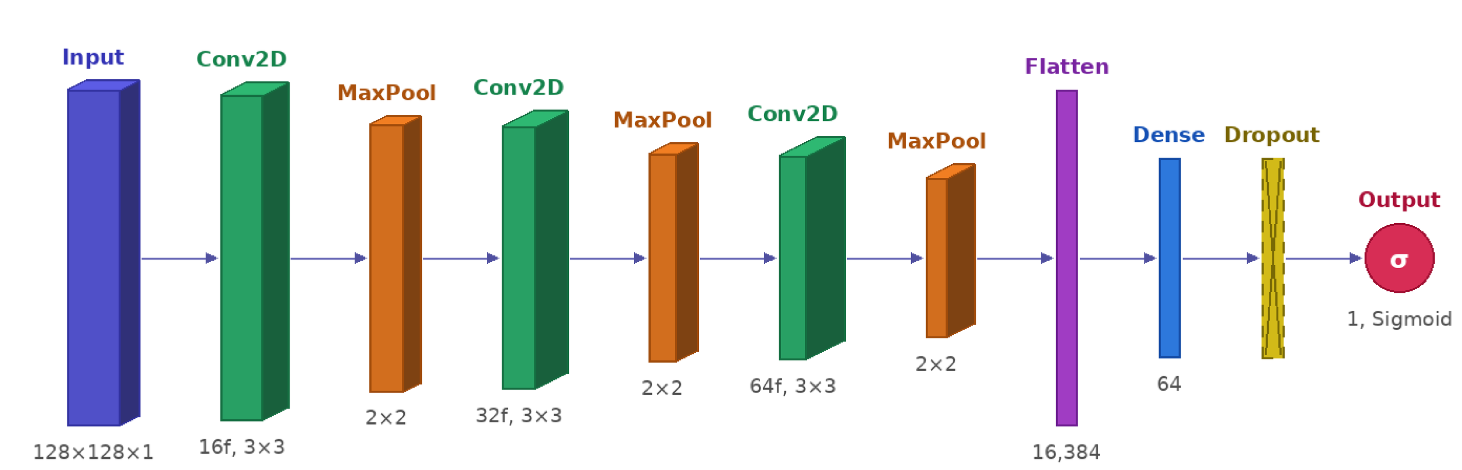

Fig 6. Architecture of the Custom CNN

DISCUSSION

Interpretation and Implications

- The supervised models outperformed unsupervised.
- CNN achieved the highest performance with 96% accuracy, significantly outperforming the unsupervised approaches. EfficientNetV2 performed near random (42% accuracy).
- The results indicate that EfficientNetV2, pre-trained on natural image datasets, exhibits limited feature transferability to grayscale thermal manufacturing data.
- The convolutional autoencoder achieved moderate performance (64% accuracy) and hybrid CAE + Isolation Forest improved separability (67% accuracy).
- This shows that unsupervised methods remain viable under limited labeled data, though they exhibit lower discriminative performance than supervised models.
- Overall, these results indicate that when labeled data is available, the best performing model is the supervised based CNN model.
- Because it provided more reliable defect detection by substantially enhancing normal–abnormal boundary learning in thermal manufacturing systems.
- Although CNN achieved the highest accuracy when defect labels were available, real-world manufacturing environments often face limited labeled data and evolving abnormal patterns.
- High performance on known defect types does not ensure robustness to unseen anomalies.
- These findings highlight the tradeoff between maximizing classification accuracy and maintaining adaptability to new abnormalities in dynamic manufacturing systems.
- Therefore, effective anomaly detection frameworks must accurately classify known defects while remaining sensitive to emergent anomaly patterns.

Study Evaluation and Future Work

- Strength: All models were evaluated using the same dataset, preprocessing pipeline, and standardized evaluation metrics (ROC, AUC, confusion matrices), ensuring a controlled and unbiased comparison.
- Limitation: The study utilized a relatively small and balanced thermal image dataset, which may not reflect class imbalance or the variability of evolving defect conditions.
- Building on these findings, future work will explore adaptive and semi-supervised frameworks to address distribution shifts and enable reliable real-time deployment in evolving manufacturing systems.

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