Machine Learning-Based Defect Detection in Laser Powder Bed Fusion Additive Manufacturing

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Introduction

What is LPBF?

Laser Powder Bed Fusion (LPBF) is a metal 3D printing process that uses a high-power laser to melt metal powder layer by layer, creating a small molten region called a melt pool. This builds complex parts directly from Computer-Aided Design (CAD) models. Used in aerospace, medical, and automotive industries.

Why Defect Detection Matters

LPBF defects cause critical part failures:

- Porosity — air pockets trapped in the metal
- Keyhole collapse — when the laser digs too deep
- Spatter — particles ejected onto the build
- Balling — irregular bead formation

In-situ (real-time) monitoring can catch these during printing.

The Problem

- Deep learning needs expensive Graphics Processing Units (GPUs) and massive datasets
- Traditional machine learning (ML) may be simpler, faster, and equally accurate
- Need: Real-time deployable monitoring

Research Question

Can traditional machine learning detect abnormal melt pools in LPBF with accuracy comparable to deep learning?

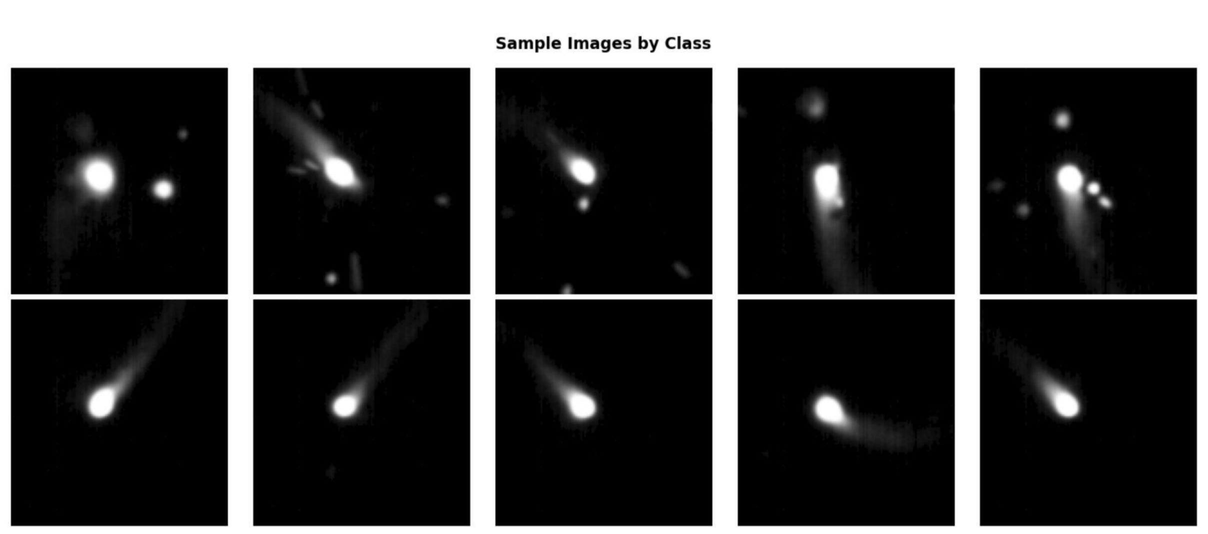

Figure 1: LPBF melt pool images — Abnormal (top) vs Normal (bottom)

Objectives

1. Build a complete image classification pipeline
2. Compare three machine learning classifiers
3. Evaluate accuracy, precision, recall, F1-score
4. Assess feasibility for real-time monitoring

Methods

Dataset: LPBF Melt Pool Images

Total Images: 1,200

Abnormal: 600 — unstable melt pools
Normal: 600 — stable melt pools

Format: Grayscale BMP, 120×120 pixels

Preprocessing Pipeline

1. Load images from labeled directories
2. Resize to 128×128 pixels
3. Convert to RGB (Red-Green-Blue) format
4. Normalize pixel values to 0–1 range
5. Flatten to 1D vectors (49,152 features)
6. Randomly shuffle data (seed=42)

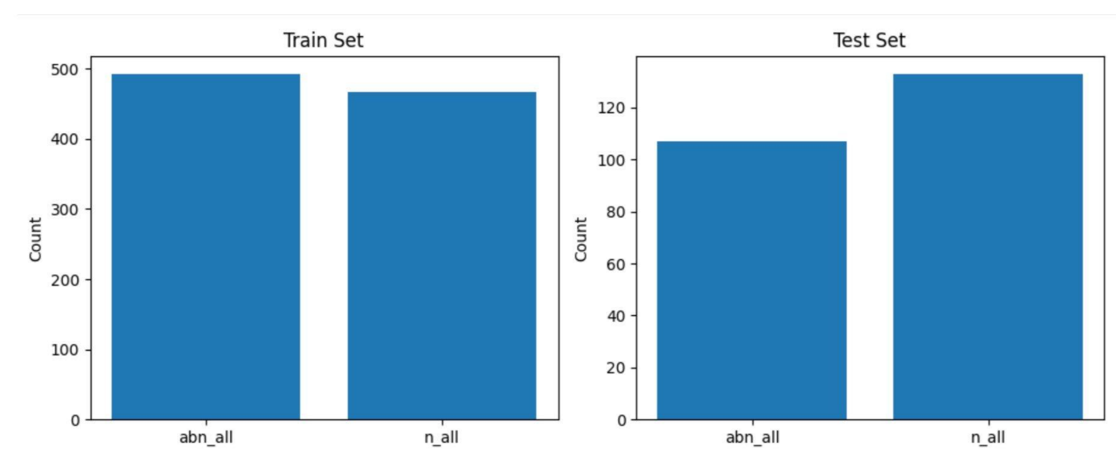

Figure 2: Train (960) / Test (240) class distribution

Classification Models

Model	What It Does
Random Forest	Combines 100 decision trees
Support Vector Machine	Finds optimal boundary between classes
Logistic Regression	Linear model for binary classification

Hyperparameters set to scikit-learn defaults; no cross-validation tuning performed.

Evaluation Metrics

- Accuracy — % of all predictions correct
- Precision — when it predicts defect, how often is it right?
- Recall — of all actual defects, how many did it catch?
- F1-Score — balance between precision and recall

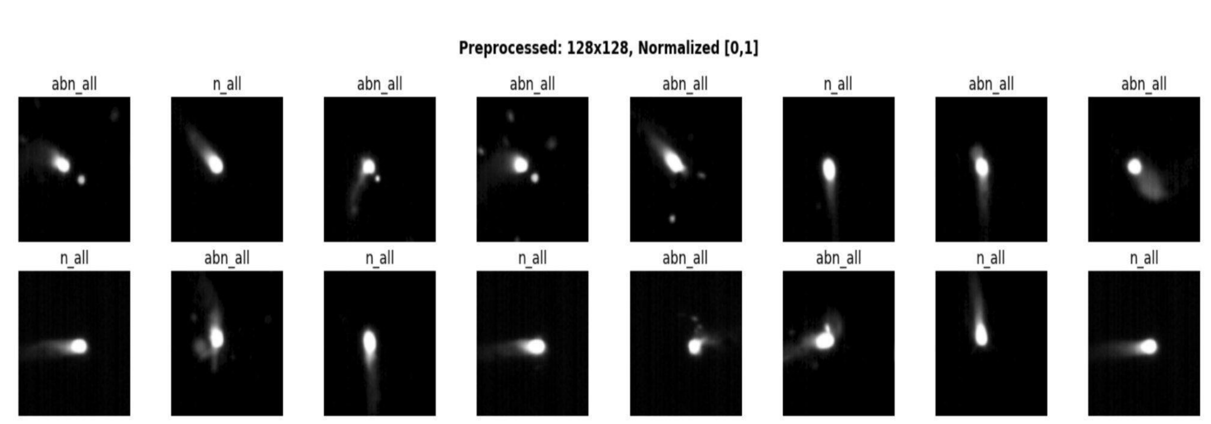

Figure 3: Preprocessed images (128×128, normalized)

Tools: Python 3.9 • NumPy • PIL • Matplotlib • scikit-learn

Results

91.25%

Best Accuracy (Random Forest)

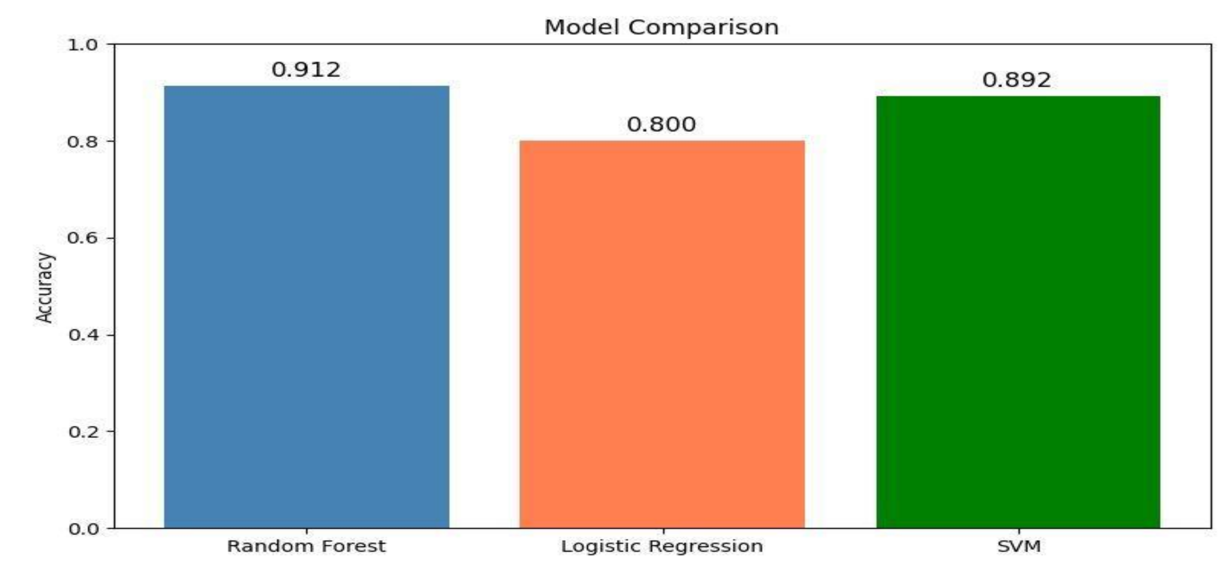

Figure 4: Model Accuracy Comparison

Model	Accuracy	F1
Random Forest	91.25%	0.91
SVM	89.17%	0.89
Logistic Reg.	80.00%	0.80

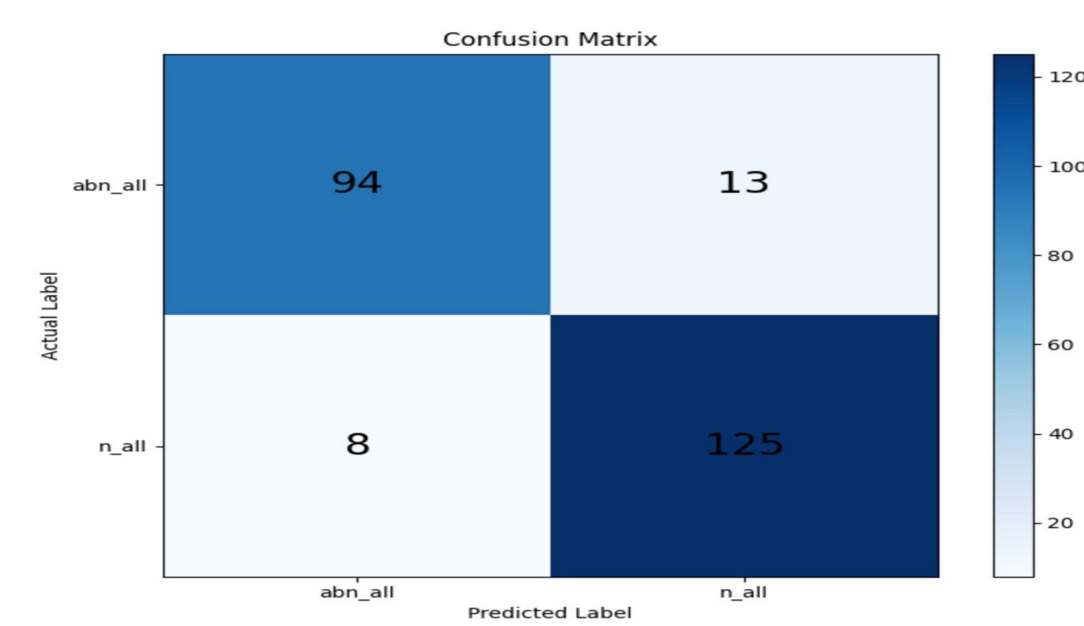

Figure 5: Confusion Matrix — shows correct vs incorrect predictions

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Classification Report:
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              precision    recall  f1-score   support

     abn_all       0.92      0.88      0.90       107
       n_all       0.91      0.94      0.92       133

    accuracy                           0.91       240
   macro avg       0.91      0.91      0.91       240
weighted avg       0.91      0.91      0.91       240
```

Figure 6: Precision, Recall, F1 by Class

Key Metrics (Random Forest)

- Abnormal: 92% precision | 88% recall | F1 0.90
- Normal: 91% precision | 94% recall | F1 0.92
- Overall: 219 of 240 test images correct

Discussion

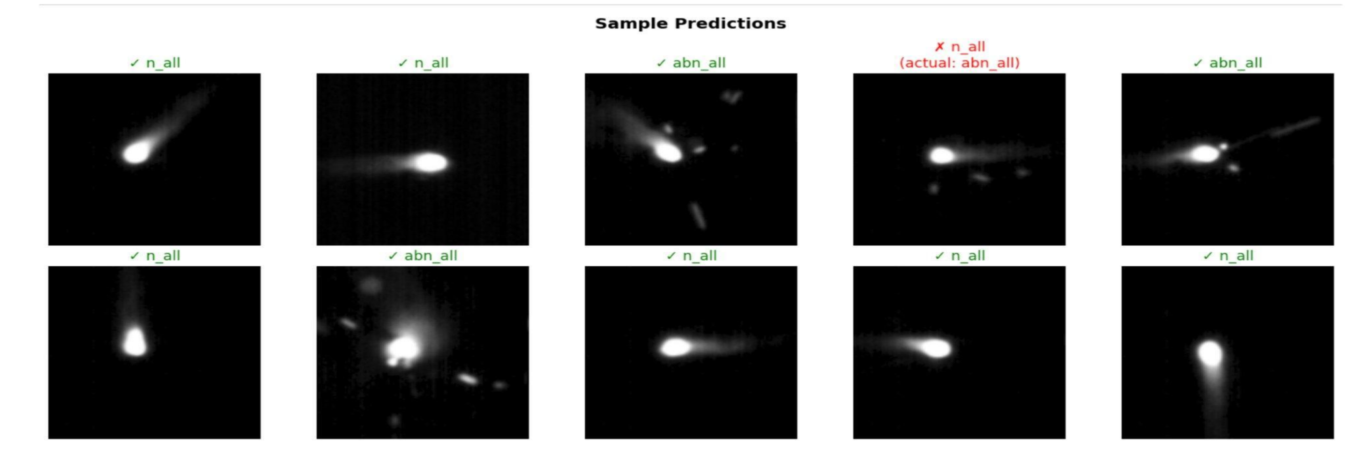

Figure 7: Sample Predictions (Green ✓ Correct, Red ✗ Wrong)

Key Findings

This study asked whether traditional ML could match deep learning for LPBF defect detection — and it can:

- Random Forest achieved 91.25% accuracy detecting melt pool anomalies
- Only 21 of 240 test images misclassified
- Model catches 94% of normal and 88% of abnormal melt pools

Significance for Additive Manufacturing

- Enables real-time quality monitoring during LPBF printing
- No GPU required — runs on low-cost edge devices (small embedded computers)
- Fast inference (<1ms per image)

Strengths & Limitations

Strengths:
- High accuracy (91.25%) with simple, interpretable models
- No GPU required — computationally efficient
- Balanced performance across both classes

Limitations:
- Limited dataset (1,200 images) may affect generalizability
- Single LPBF system and material tested
- Binary classification only (defect vs. no defect)

Future Work

- Multi-class classification (porosity, keyhole, spatter)
- Test across materials: Ti-6Al-4V, IN718, SS316L
- Compare with Convolutional Neural Networks (CNNs)
- Real-time closed-loop process control

References

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