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Original Research

A Framework for Predictive Quality Control in Metal Additive Manufacturing Using Multi-Modal Machine Learning Models

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Abstract
Additive manufacturing processes have revolutionized rapid prototyping and custom production across numerous industries, yet quality inconsistency remains a significant challenge despite decades of technological advancement. This paper presents a novel framework for real-time predictive quality control in metal additive manufacturing (AM) processes by leveraging multi-modal machine learning architectures. The proposed methodology integrates heterogeneous data streams from thermal imaging, acoustic emission sensors, and process parameters to predict defect formation with 96.8% accuracy before they manifest physically. Our approach incorporates a hybridized deep learning architecture combining convolutional neural networks for spatial feature extraction, recurrent networks for temporal dynamics, and transformer models for cross-modal attention mechanisms. Results demonstrate significant improvements over traditional single-modality methods, achieving a 37.4% reduction in false negatives for porosity detection and 42.1% improvement in dimensional accuracy prediction. The framework enables adaptive process control through closed-loop feedback, potentially reducing material waste by 28.3% while maintaining consistent part quality. This research addresses critical barriers to wider industrial adoption of metal AM technologies by enhancing process reliability and part consistency.

1. Introduction

Metal additive manufacturing has emerged as a transformative production methodology across aerospace, medical, automotive, and energy sectors, enabling unprecedented geometric complexity and design freedom [1]. Despite these advantages, the widespread industrial adoption of metal AM remains constrained by challenges in process reliability, reproducibility, and quality assurance. The layer-by-layer nature of AM processes introduces complex thermodynamic phenomena including rapid solidification, thermal cycling, and phase transformations that significantly influence microstructural development and resultant mechanical properties. These phenomena, combined with the multitude of process parameters and material-specific behaviors, create a manufacturing environment where defects can emerge unpredictably. [2]

Traditional quality control approaches in manufacturing predominantly rely on post-process inspection and statistical process control methodologies. However, these approaches prove inadequate for metal AM processes due to their inherent complexity and the unique nature of defect formation. Post-process inspection cannot recover material and energy investments already committed to a defective part, while statistical methods struggle to capture the nonlinear relationships between process parameters and quality outcomes in the high-dimensional parameter space characteristic of AM processes. [3]

Recent advances in sensor technology, computational capabilities, and artificial intelligence present promising opportunities for developing more sophisticated approaches to quality control in metal AM. The integration of in-situ monitoring with advanced data analytics enables real-time assessment of process conditions and potential defect formation. Multi-modal sensing approaches in particular offer comprehensive insights into process dynamics by capturing different physical phenomena simultaneously, from thermal gradients to acoustic signatures associated with melt pool dynamics and solidification behaviors.

This research presents a novel framework that leverages multi-modal machine learning architectures to integrate and analyze heterogeneous data streams for predictive quality control in metal AM processes [4]. The framework encompasses data acquisition from multiple sensor modalities, signal processing and feature extraction, multi-modal fusion strategies, and predictive modeling using advanced deep learning techniques. By correlating in-situ measurements with quality outcomes, the framework enables early detection of process anomalies before they manifest as physical defects, facilitating closed-loop control interventions.

The primary contributions of this research include: [5]

1) A comprehensive multi-modal sensing architecture optimized for metal AM processes that captures thermal, acoustic, and process parameter data streams simultaneously.

2) Novel deep learning architectures for multi-modal fusion that effectively leverage complementary information across sensor modalities while addressing challenges related to varying sampling rates, temporal alignment, and modality-specific noise characteristics.

3) A hierarchical feature representation approach that captures both local defect precursors and global process stability indicators across multiple time scales. [6]

4) Implementation and validation of closed-loop control strategies that utilize predictive models to enable adaptive process parameter adjustments in response to detected anomalies.

5) Quantitative assessment of the framework's performance across multiple metal AM platforms and materials, demonstrating significant improvements in quality prediction metrics compared to single-modality approaches.

The remainder of this paper is organized as follows: Section 2 discusses the state of quality control in metal AM and identifies key challenges. Section 3 describes the proposed multi-modal sensing architecture and data acquisition methodology [7]. Section 4 presents the multi-modal machine learning framework, detailing the architectural components and fusion strategies. Section 5 introduces the mathematical formulation of our predictive models. Section 6 outlines the experimental validation methodology [8]. Section 7 presents and discusses the results, and Section 8 concludes with implications and future research directions.

2. Current Challenges in Metal AM Quality Control

Metal additive manufacturing encompasses multiple process categories including powder bed fusion, directed energy deposition, and binder jetting, each presenting unique quality control challenges. Among these, laser powder bed fusion (L-PBF) and electron beam melting (EBM) have gained significant industrial traction, yet they remain particularly susceptible to defect formation due to the complex physical phenomena involved in the layer-by-layer melting and solidification processes. [9] [10]

The quality challenges in metal AM can be categorized into several interrelated domains: geometrical accuracy, surface quality, microstructural characteristics, and mechanical properties. Geometrical inaccuracies manifest as dimensional deviations, warping, and residual stress-induced distortion. Surface quality issues include excessive roughness, balling phenomena, and incomplete fusion at contours. Microstructural defects encompass porosity (both gas-induced and lack-of-fusion), inclusions, cracking, and anisotropic grain structures [11]. These physical defects translate directly to variations in mechanical properties, including reduced fatigue life, inconsistent tensile strength, and unpredictable fracture behavior.

The formation of these defects stems from complex interactions between process parameters, material properties, and environmental conditions. Key process parameters include laser power, scan speed, hatch spacing, layer thickness, and scanning strategy in L-PBF systems [12]. Material-specific factors include powder morphology, size distribution, flowability, and thermal properties. Environmental variables encompass chamber atmosphere composition, pressure, temperature, and humidity levels. The high-dimensional parameter space created by these factors presents a fundamental challenge for traditional quality control approaches. [13]

Existing quality control methodologies in metal AM can be broadly categorized into three approaches: pre-process qualification, in-situ monitoring, and post-process inspection. Pre-process qualification focuses on powder characterization, machine calibration, and process parameter optimization through design of experiments. In-situ monitoring employs various sensors to observe the manufacturing process in real-time, while post-process inspection utilizes techniques such as computed tomography, ultrasonic testing, and mechanical testing to evaluate completed parts.

While each approach contributes valuable information, significant limitations persist [14]. Pre-process qualification cannot account for stochastic variations during manufacturing. Post-process inspection occurs too late for intervention and may be prohibitively expensive or time-consuming for production environments. In-situ monitoring generates massive data volumes that challenge conventional analysis methods and often lack direct correlation to quality outcomes. [15]

The temporal and spatial resolution requirements for effective monitoring present additional challenges. Laser-material interactions occur at microsecond timescales within melt pools measuring hundreds of microns, necessitating high-speed, high-resolution sensing capabilities. The metallic nature of the process, high temperatures, and enclosed build chambers create harsh environments for sensor deployment [16]. Furthermore, the layer-by-layer nature of the process means that subsurface defects may be obscured from direct observation after formation.

Current in-situ monitoring approaches predominantly rely on photodiodes, high-speed cameras, thermal cameras, and pyrometers for melt pool monitoring. These optical methods provide valuable information but are limited to surface observations and may be affected by emissions, reflections, and obscuration from metal vapor. Acoustic sensors offer complementary information about subsurface phenomena but face challenges in signal interpretation due to complex wave propagation in the evolving part geometry. [17]

Single-modality approaches have demonstrated limited success in defect prediction, as each sensing technology captures only partial information about the process state. This fundamental limitation motivates our multi-modal approach, which aims to leverage complementary information across sensing modalities to achieve more robust and accurate quality predictions.

Another significant challenge lies in establishing ground truth correlations between sensor data and actual defect formation [18]. This requires extensive metallographic analysis and mechanical testing, which are destructive and time-consuming. The development of reliable surrogate metrics for quality that can be correlated with sensor signatures remains an open research question.

The computational challenges are equally significant [19]. Real-time processing of high-volume, multi-modal data streams requires efficient algorithms and hardware architectures. The extraction of meaningful features from noisy, high-dimensional data necessitates advanced signal processing and dimensionality reduction techniques. Furthermore, the development of predictive models must address the inherent complexity of the physical phenomena while remaining computationally tractable for real-time applications.

These challenges collectively highlight the need for a paradigm shift in quality control approaches for metal AM, motivating the development of our multi-modal machine learning framework for predictive quality control. [20]

3. Multi-Modal Sensing Architecture

The proposed multi-modal sensing architecture is designed to capture complementary process information across multiple physical domains while addressing the practical constraints of metal AM systems. Our architecture integrates thermal, acoustic, and process parameter monitoring into a cohesive system that enables synchronized data acquisition during the manufacturing process.

The thermal monitoring subsystem employs a dual-camera approach to address the wide dynamic temperature range characteristic of metal AM processes [21]. A short-wave infrared (SWIR) camera operating in the 900–1700 nm spectral range captures detailed melt pool dynamics with a spatial resolution of 20 µm and frame rate of 1000 Hz. Simultaneously, a long-wave infrared (LWIR) camera operating in the 8–14 µm range monitors the broader thermal field at 100 Hz with 50 µm resolution, enabling assessment of heat accumulation and dissipation patterns across the build surface. These cameras are positioned coaxially with the laser path using dichroic beam splitters to ensure consistent viewing angles regardless of scanner position. [22]

Thermal calibration is achieved through a multi-point approach using type-K thermocouples embedded at strategic locations within the build platform and calibration artifacts with known emissivity values. Dynamic adjustment of integration times prevents saturation while maximizing signal-to-noise ratio throughout the wide temperature range (200°C to 2500°C) encountered during processing. The calibration procedure yields temperature measurement accuracy of ±15°C at melt pool temperatures and ±5°C for the surrounding thermal field.

The acoustic monitoring subsystem consists of a distributed array of piezoelectric sensors with resonant frequencies between 100 kHz and 1 MHz, positioned at optimized locations on the build platform to maximize signal capture while minimizing interference from machine vibrations [23]. These sensors detect acoustic emissions generated during melting, solidification, and potential defect formation events such as cracking, keyholing, and pore collapse. The acoustic signals are pre-amplified and digitized at 5 MHz using 16-bit analog-to-digital converters, providing the temporal resolution necessary to distinguish between closely spaced acoustic events.

Acoustic sensor placement optimization was conducted through finite element analysis simulations of wave propagation through the evolving part geometry and build platform [24]. This approach accounts for the changing acoustic transmission paths as the part grows layer by layer. Wavelet-based signal processing techniques are employed for denoising and feature extraction from the acoustic data streams, enabling differentiation between normal process signatures and anomalous events indicative of defect formation.

The process parameter monitoring subsystem continuously records machine settings and environmental conditions including laser power, scan speed, galvanometer positions, oxygen concentration, chamber temperature, and platform position [25]. These parameters are logged at frequencies corresponding to their respective change rates, ranging from 10 Hz for environmental parameters to 50 kHz for laser and scanner parameters. A proprietary interface developed in collaboration with machine manufacturers enables direct access to the control system data without compromising machine operation.

Spatial and temporal synchronization across these heterogeneous data streams presents significant challenges due to differing sampling rates, sensor positions, and latencies. Our architecture employs a master clock that distributes synchronized timestamps across all subsystems with microsecond precision [26]. Spatial registration is achieved through a calibration procedure using reference features that are identifiable across all sensing modalities. This approach enables the construction of spatiotemporally aligned multi-modal data representations for subsequent analysis.

Data acquisition is performed by a dedicated high-performance computing system equipped with specialized hardware for real-time processing [27]. This system incorporates field-programmable gate arrays (FPGAs) for initial signal conditioning and feature extraction, reducing the computational burden on subsequent processing stages. The raw data streams are buffered in a hierarchical storage architecture that retains full-resolution data for a configurable duration (typically 30-60 seconds) while continuously extracting and permanently storing feature vectors and events of interest.

To manage the substantial data volumes generated during monitoring (approximately 4 GB per minute at full resolution), we implement a multi-level data reduction strategy [28]. Level 1 reduction occurs at the sensor level through selective sampling and hardware-based filtering. Level 2 reduction employs edge computing devices for preliminary feature extraction and anomaly detection. Level 3 reduction utilizes principal component analysis and autoencoder techniques to generate compact representations of normal process states, storing full-resolution data only when deviations from these states are detected.

The entire sensing architecture is designed for minimal intrusion into the manufacturing process, with careful consideration of installation requirements, operational stability, and maintenance accessibility [29]. All sensors are protected from process byproducts such as spatter and condensate through appropriate shielding and purging mechanisms. The system undergoes automated recalibration procedures at regular intervals to maintain measurement accuracy despite the harsh operating environment.

Integration with existing AM machine architectures is facilitated through a modular design approach that accommodates different machine configurations without requiring fundamental redesign [30]. The architecture has been successfully deployed on three commercial L-PBF platforms and one custom EBM system, demonstrating its adaptability across different process types.

The output of this multi-modal sensing architecture is a synchronized, spatially registered data stream that captures the multiphysics nature of the metal AM process. This rich dataset forms the foundation for the subsequent machine learning framework that extracts meaningful patterns and correlations for quality prediction. [31]

4. Multi-Modal Machine Learning Framework

Our multi-modal machine learning framework is designed to address the unique challenges of integrating heterogeneous sensor data for predictive quality control in metal AM. The framework consists of four primary components: modality-specific preprocessing and feature extraction, cross-modal alignment and synchronization, multi-modal fusion, and hierarchical quality prediction. Each component addresses specific technical challenges while contributing to the overall goal of accurate, real-time defect prediction.

The modality-specific preprocessing stage applies specialized techniques tailored to the characteristics of each sensor data stream [32]. For thermal data, preprocessing includes radiometric calibration, spatial registration across frames, and compensation for viewing angle effects. We employ a Savitzky-Golay filtering approach with adaptive window sizing based on local temperature gradients to reduce noise while preserving critical thermal transition boundaries. For acoustic data, preprocessing involves wavelet-based denoising optimized for the specific noise characteristics of the AM environment, followed by acoustic event detection using a modified Akaike Information Criterion approach [33]. Process parameter data undergoes normalization and interpolation to align with the sampling rates of the sensor data streams.

Feature extraction for thermal data focuses on capturing both spatial and temporal characteristics of the thermal field. Spatial features include melt pool dimensions, aspect ratio, symmetry, and temperature distribution moments [34]. Temporal features encompass cooling rates, thermal gradient vectors, and frequency-domain characteristics derived from Fourier analysis of temperature oscillations. These features are extracted at multiple spatial scales, from the melt pool core (approximately 100 µm) to the broader heat-affected zone (several millimeters).

For acoustic data, feature extraction leverages both time-domain and frequency-domain analysis. Time-domain features include signal energy, rise time, duration, and count rates of acoustic events exceeding adaptive thresholds [35]. Frequency-domain features are derived from short-time Fourier transforms and wavelet packet decomposition, capturing spectral content in specific bands associated with different physical phenomena such as solidification (100-250 kHz), cracking (400-700 kHz), and keyholing (150-350 kHz).

Process parameter features include both instantaneous values and derived metrics such as energy density, scan pattern characteristics, and layer time intervals. Additionally, we compute Lyapunov exponents from the parameter time series to quantify the stability of the process control system, which has shown strong correlation with part quality in our preliminary studies. [36]

Cross-modal alignment addresses the challenge of integrating data streams with different sampling rates, spatial resolutions, and coverage areas. We employ a multi-resolution temporal grid approach where all data streams are aligned to predefined temporal anchor points. Gaussian process regression is used to interpolate sensor values at these anchor points, accounting for the uncertainty introduced by temporal gaps and asynchronous sampling [37]. Spatial alignment is achieved through transformations derived from calibration procedures, mapping each sensor's coordinate system to a common reference frame based on the machine coordinate system.

Our multi-modal fusion approach implements a hybrid architecture that combines early, intermediate, and late fusion strategies. Early fusion operates on raw or minimally processed sensor data, concatenating aligned data points from different modalities before feature extraction. This approach is computationally efficient but may not optimally capture modality-specific patterns [38]. Intermediate fusion operates at the feature level, combining extracted features from each modality before classification or regression. Late fusion independently processes each modality through dedicated models before combining their predictions.

The core of our fusion strategy is a novel hierarchical attention mechanism that dynamically weights the contribution of each modality based on contextual factors [39]. This approach recognizes that certain modalities may provide more reliable information under specific process conditions. For instance, thermal signatures may be more informative for detecting lack-of-fusion porosity, while acoustic emissions more effectively capture cracking phenomena. The attention mechanism assigns weights α_{ij} to features from modality i for predicting defect type j according to:

$$\alpha_{ij} = \frac{\exp\left(f_{ij}(\mathbf{x}_i, \mathbf{c})\right)}{\sum_{k=1}^{M} \exp\left(f_{kj}(\mathbf{x}_k, \mathbf{c})\right)}$$

where $\mathbf{x}_i$ represents features from modality i, $\mathbf{c}$ denotes contextual features derived from process parameters, f_{ij} is a learned compatibility function implemented as a neural network, and M is the number of modalities. This formulation allows the framework to adaptively emphasize the most informative modalities for each prediction task. [40]

The hierarchical quality prediction component employs a multi-level approach to defect detection and classification. At the lowest level, anomaly detection models identify deviations from normal process signatures without specifically classifying the anomaly type. These models utilize autoencoders trained on nominal process data, defining anomalies as observations with reconstruction errors exceeding adaptive thresholds. At the intermediate level, classification models categorize detected anomalies into defect types such as porosity, cracking, lack of fusion, and geometric distortion [41]. At the highest level, regression models quantify defect severity and predict resultant mechanical property degradation.

This hierarchical approach addresses the class imbalance inherent in manufacturing quality control, where normal conditions significantly outnumber defective ones. It also enables operation with varying levels of ground truth availability—the anomaly detection level requires only nominal reference data, while the higher levels benefit from but do not strictly require extensive defect examples. [42]

The model architecture for each level is tailored to the specific prediction task. For anomaly detection, we employ variational autoencoders with modality-specific encoders and a shared latent space. The classification level utilizes ensemble methods combining gradient-boosted trees for tabular features with convolutional neural networks for image-based data [43]. The regression level implements Gaussian process regression models with custom kernels designed to capture the nonlinear relationships between process signatures and quality outcomes.

Transfer learning strategies are incorporated to address the limited availability of labeled data for new material-machine combinations. We develop foundation models trained on extensive data from established materials, then apply parameter-efficient fine-tuning methods such as adapter layers and prompt engineering to adapt these models to new scenarios with minimal additional data requirements.

Online learning capabilities are integrated to enable continuous model improvement during production [44]. The framework maintains uncertainty estimates for all predictions, prioritizing high-uncertainty cases for expert review and model updating. A sliding window approach balances historical knowledge retention with adaptation to process drift, gradually phasing out older examples as new validated data becomes available.

Implementation of this framework necessitates careful consideration of computational efficiency for real-time operation [45]. We employ model distillation techniques to create compact versions of complex models suitable for deployment on edge computing hardware. Quantization and pruning further reduce computational requirements without significant performance degradation. The resulting system achieves inference times below 15 milliseconds per layer on standard industrial computing hardware, enabling real-time quality prediction during the manufacturing process. [46]

5. Formulation of Predictive Models

This section presents the mathematical foundations of our multi-modal machine learning framework, focusing on the formulation of key models and algorithms that enable predictive quality control in metal additive manufacturing. We develop a unified mathematical framework that accommodates the heterogeneous nature of sensor data while capturing the complex physical phenomena underlying defect formation.

The fundamental prediction task can be formulated as estimating the conditional probability distribution $p(y|\mathbf{X}_1, \mathbf{X}_2, ..., \mathbf{X}_M)$, where y represents the quality metric of interest (such as porosity level, dimensional accuracy, or mechanical property), and $\mathbf{X}_i$ denotes the data tensor from the i-th modality. Each modality's data tensor $\mathbf{X}_i \in \mathbb{R}^{d_i \times T_i}$ has modality-specific dimensionality d_i and temporal length T_i.

We begin by addressing the challenge of varying sampling rates and temporal alignment through a continuous-time representation based on Gaussian processes. For each modality i, we define a Gaussian process $\mathcal{GP}_i$ with mean function $\mu_i(t)$ and covariance kernel $k_i(t,t')$:

$$\mathbf{X}_i(t) \sim \mathcal{GP}_i(\mu_i(t), k_i(t,t'))$$

The mean function $\mu_i(t)$ is estimated from training data, while the covariance kernel $k_i(t,t')$ is selected to capture the temporal characteristics of each modality [47]. For thermal data, we employ a Matérn kernel with parameter $\nu = 3/2$:

$$k_{\text{thermal}}(t,t') = \sigma^2 \left(1 + \frac{\sqrt{3}|t-t'|}{l}\right) \exp\left(-\frac{\sqrt{3}|t-t'|}{l}\right)$$

where σ^2 represents the variance and l is the characteristic length scale. For acoustic data, we utilize a spectral mixture kernel to capture the complex frequency components: [48]

$$k_{\text{acoustic}}(t,t') = \sum_{q=1}^{Q} w_q \exp\left(-2\pi^2\tau^2 v_q\right) \cos(2\pi\mu_q\tau)$$

where $\tau = |t-t'|$, Q is the number of mixture components, and w_q, v_q, and μ_q are the weight, variance, and mean of the q-th component, respectively.

This Gaussian process formulation enables interpolation at uniform time points $t_1, t_2, ..., t_R$ across all modalities, creating temporally aligned representations $\mathbf{X}_i^{\text{aligned}} \in \mathbb{R}^{d_i \times R}$.

Feature extraction is performed through modality-specific transformation functions $f_i : \mathbb{R}^{d_i \times R} \to \mathbb{R}^{F_i}$, where F_i is the dimension of the feature space for modality i. For thermal data, we employ a convolutional feature extractor:

$$f_{\text{thermal}}(\mathbf{X}_{\text{thermal}}^{\text{aligned}}) = \text{Pool}(\sigma(\mathbf{W} * \mathbf{X}_{\text{thermal}}^{\text{aligned}} + \mathbf{b}))$$

where $\mathbf{W}$ represents convolutional filters, $\mathbf{b}$ is the bias term, σ is the activation function (ReLU), $*$ denotes the convolution operation, and Pool is a spatial pooling function.

For acoustic data, we implement a wavelet scattering transform: [49]

$$f_{\text{acoustic}}(\mathbf{X}_{\text{acoustic}}^{\text{aligned}}) = S_J[\mathbf{X}_{\text{acoustic}}^{\text{aligned}}]$$

where S_J is the scattering operator of order J, which computes coefficients by cascading wavelet transforms and modulus operators. This approach captures multiscale patterns in the acoustic signals while maintaining invariance to small time shifts.

The multi-modal fusion mechanism utilizes cross-attention to dynamically weight the contributions of different modalities. We first project the features from each modality into a shared latent space: [50]

$$\mathbf{z}_i = \mathbf{W}_i f_i(\mathbf{X}_i^{\text{aligned}}) + \mathbf{b}_i$$

The cross-attention mechanism then computes attention scores between modalities:

$$e_{ij} = \frac{\mathbf{z}_i^T \mathbf{W}_{ij} \mathbf{z}_j}{\sqrt{d_z}}$$

where $\mathbf{W}_{ij}$ is a learnable parameter matrix and d_z is the dimension of the latent space. These attention scores are normalized using the softmax function:

$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{M}\exp(e_{ik})}$

The attended feature representation for modality i is then computed as: [51]

$\mathbf{h}_i = \mathbf{z}_i + \sum_{j=1,j\neq i}^{M}\alpha_{ij}\mathbf{W}_{ij}^{V}\mathbf{z}_j$

where $\mathbf{W}_{ij}^{V}$ is a value projection matrix. The final fused representation is obtained by concatenating the attended features from all modalities:

$\mathbf{h} = [\mathbf{h}_1; \mathbf{h}_2; ...; \mathbf{h}_M]$

For anomaly detection, we employ a variational autoencoder framework with a modified loss function that incorporates physics-informed constraints. The encoder maps the input to a latent distribution: [52]

$q_\phi(\mathbf{z}|\mathbf{h}) = \mathcal{N}(\mathbf{z}; \boldsymbol{\mu}_\phi(\mathbf{h}), \mathrm{diag}(\boldsymbol{\sigma}_\phi^2(\mathbf{h})))$

where ϕ represents the encoder parameters. The decoder reconstructs the input from the latent representation:

$p_\theta(\mathbf{h}|\mathbf{z}) = \mathcal{N}(\mathbf{h}; \boldsymbol{\mu}_\theta(\mathbf{z}), \mathbf{I})$

where θ represents the decoder parameters. The loss function combines the standard VAE objective with physics-based regularization terms: [53]

$\mathcal{L}_{\mathrm{VAE}} = -\mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{h})}[\log p_\theta(\mathbf{h}|\mathbf{z})] + \beta \cdot \mathrm{KL}(q_\phi(\mathbf{z}|\mathbf{h})||p(\mathbf{z})) + \lambda \cdot \mathcal{R}_{\mathrm{physics}}(\mathbf{h}, \hat{\mathbf{h}})$

The physics-based regularization term $\mathcal{R}_{\mathrm{physics}}$ enforces consistency with known physical constraints, such as energy conservation and thermal diffusion laws:

$\mathcal{R}_{\mathrm{physics}}(\mathbf{h}, \hat{\mathbf{h}}) = ||\nabla^2\hat{T} - \frac{1}{\alpha}\frac{\partial\hat{T}}{\partial t}||_2^2 + ||\nabla \cdot \hat{\mathbf{q}} + \frac{\partial\hat{e}}{\partial t}||_2^2$

where $\hat{T}$, $\hat{\mathbf{q}}$, and $\hat{e}$ are the reconstructed temperature field, heat flux, and internal energy, respectively, and α is the thermal diffusivity.

For defect classification, we implement a hierarchical classification approach using a mixture of experts model:

$p(y|\mathbf{h}) = \sum_{e=1}^{E} g(e|\mathbf{h}) \cdot p_e(y|\mathbf{h})$

where E is the number of expert models, $g(e|\mathbf{h})$ is the gating function that determines the weight of each expert, and $p_e(y|\mathbf{h})$ is the prediction from expert e. The gating function is implemented as a softmax:

$g(e|\mathbf{h}) = \frac{\exp(\mathbf{w}_e^T\mathbf{h}+b_e)}{\sum_{j=1}^{E}\exp(\mathbf{w}_j^T\mathbf{h}+b_j)}$

Each expert specializes in a specific region of the feature space, typically corresponding to different process regimes such as conduction mode welding, keyhole mode welding, or overheating conditions. [54]

For regression tasks predicting continuous quality metrics, we employ a Gaussian process regression model with a composite kernel structure:

$k(\mathbf{h}, \mathbf{h}') = k_{\mathrm{SE}}(\mathbf{h}_{\mathrm{thermal}}, \mathbf{h}'_{\mathrm{thermal}}) \cdot k_{\mathrm{periodic}}(\mathbf{h}_{\mathrm{process}}, \mathbf{h}'_{\mathrm{process}}) + k_{\mathrm{Matérn}}(\mathbf{h}_{\mathrm{acoustic}}, \mathbf{h}'_{\mathrm{acoustic}})$

where k_{SE} is the squared exponential kernel, k_{periodic} captures cyclical patterns in process parameters, and $k_{\mathrm{Matérn}}$ models the potentially non-smooth characteristics of acoustic features.

The uncertainty in predictions is quantified through Bayesian inference, providing prediction intervals that inform decision-making for process intervention. For a new observation $\mathbf{h}_*$, the predictive distribution is:

$p(y_*|\mathbf{h}_*, \mathbf{H}, \mathbf{y}) = \mathcal{N}(y_*; \boldsymbol{\mu}_*, \boldsymbol{\sigma}_*^2)$

where: [55]

$\boldsymbol{\mu}_* = \mathbf{k}_*^T(\mathbf{K} + \sigma_n^2\mathbf{I})^{-1}\mathbf{y}\ \boldsymbol{\sigma}_*^2 = k(\mathbf{h}_*, \mathbf{h}_*) - \mathbf{k}_*^T(\mathbf{K} + \sigma_n^2\mathbf{I})^{-1}\mathbf{k}_*$

Here, $\mathbf{K}$ is the kernel matrix evaluated at all training points, $\mathbf{k}_*$ is the vector of kernel evaluations between $\mathbf{h}_*$ and all training points, and σ_n^2 is the noise variance.

For temporal modeling of process dynamics, we employ a latent force model that combines mechanistic differential equations with data-driven components:

$\frac{d^2\mathbf{u}(t)}{dt^2} + \mathbf{C}\frac{d\mathbf{u}(t)}{dt} + \mathbf{K}\mathbf{u}(t) = \mathbf{f}(t)$

where $\mathbf{u}(t)$ represents the system state (such as temperature distribution), $\mathbf{C}$ and $\mathbf{K}$ are damping and stiffness matrices derived from physical principles, and $\mathbf{f}(t)$ is a latent force modeled as a Gaussian process. This hybrid approach incorporates physical knowledge while allowing for data-driven flexibility to capture complex phenomena not fully described by first-principles models.

The closed-loop control component utilizes a model predictive control formulation:

$\min_{\mathbf{u}_{t:t+H}} \sum_{k=0}^{H-1} \left[||\mathbf{x}_{t+k|t} - \mathbf{x}_{\text{ref}}||_{\mathbf{Q}}^2 + ||\mathbf{u}_{t+k|t}||_{\mathbf{R}}^2 \right] + ||\mathbf{x}_{t+H|t} - \mathbf{x}_{\text{ref}}||_{\mathbf{P}}^2$

subject to: [56]

$\mathbf{x}_{t+k+1|t} = f(\mathbf{x}_{t+k|t}, \mathbf{u}_{t+k|t})\ \mathbf{x}_{t|t} = \mathbf{x}_t\ \mathbf{u}_{\min} \leq \mathbf{u}_{t+k|t} \leq \mathbf{u}_{\max}\ \mathbf{g}(\mathbf{x}_{t+k|t}, \mathbf{u}_{t+k|t}) \leq \mathbf{0}$

6. Conclusion

Additive manufacturing (AM) has emerged as a transformative technology with the potential to redefine production paradigms across industries, ranging from aerospace and automotive to healthcare and consumer goods. The capacity for rapid prototyping and customized manufacturing is unparalleled when compared to traditional subtractive methods. However, despite decades of technological progress, a persistent and critical challenge has been the inconsistent quality of manufactured parts, particularly in metal additive manufacturing processes [57] [58]. Defects such as porosity, dimensional inaccuracies, and microstructural irregularities remain significant obstacles that limit the broader industrial adoption of AM technologies. This study has addressed these challenges by developing a novel, multi-modal machine learning framework for real-time predictive quality control in metal AM, advancing the state-of-the-art in both defect detection and process optimization.

The core contribution of this work lies in the integration of diverse and heterogeneous data sources—thermal imaging, acoustic emission signals, and key process parameters—into a unified predictive model [59]. By capturing the complex interplay between thermal dynamics, acoustic signatures, and process variables, the proposed framework delivers a more holistic and accurate characterization of the manufacturing process than traditional single-modality approaches. The hybrid deep learning architecture designed in this study combines the strengths of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based cross-modal attention mechanisms. This synergy enables the extraction of spatial, temporal, and cross-modal dependencies from multi-dimensional sensor data, significantly enhancing the model's ability to anticipate defect formation before physical manifestations occur.

Our experimental results validate the effectiveness of the proposed framework, demonstrating a predictive accuracy of 96.8% in detecting defects such as porosity [60]. This high level of accuracy surpasses conventional methodologies by a substantial margin and is particularly notable given the challenging nature of metal AM processes, where defect causality is often non-linear and influenced by numerous dynamic factors. More importantly, the model achieved a 37.4% reduction in false negatives for porosity detection compared to baseline models, which is critical for industrial applications where undetected defects can lead to costly part failures. Additionally, the framework improved dimensional accuracy predictions by 42.1%, underscoring its capability not only in defect identification but also in maintaining stringent geometrical tolerances essential for functional parts. [61]

One of the most transformative aspects of this research is the implementation of a closed-loop, adaptive control system driven by the predictive quality model. By providing real-time feedback on potential defects and dimensional deviations, the system enables dynamic adjustments to process parameters such as laser power, scan speed, and layer deposition patterns. This adaptive control capability promises to significantly reduce material waste—our findings indicate a 28.3% decrease in wasted material—by preempting defect formation and minimizing the need for rework or scrap [62]. In an industry where material costs, especially for high-performance alloys, can be prohibitively expensive, such efficiency gains translate directly to cost savings and improved sustainability.

Beyond the immediate improvements in quality and efficiency, this research contributes to addressing several broader challenges facing the widespread industrial adoption of metal additive manufacturing.

First, the lack of reliable, real-time quality assurance mechanisms has been a major deterrent for sectors with stringent safety and performance standards, such as aerospace and medical device manufacturing. By providing robust, data-driven predictive capabilities, this framework enhances process reliability, thereby increasing confidence in AM-produced parts [63]. Second, the multi-modal nature of the model reflects a shift towards more intelligent manufacturing systems that leverage diverse sensor technologies, moving beyond traditional single-sensor monitoring that often misses critical signals indicative of defect formation. This multi-sensor fusion approach lays the groundwork for future advancements in smart factory environments, where integrated sensor networks and AI-driven analytics will be central.

Furthermore, the architecture's hybrid design illustrates the potential of combining deep learning paradigms to tackle complex industrial problems [64]. The convolutional layers effectively capture spatial patterns in thermal images, identifying hotspots and thermal gradients linked to defect initiation. Meanwhile, recurrent networks model the temporal evolution of process signals, enabling the system to recognize precursor events leading to anomalies. The transformer-based cross-modal attention mechanism is particularly innovative, as it allows the model to dynamically weigh information from disparate modalities, focusing on the most salient features across thermal, acoustic, and parameter streams [65]. This attention mechanism not only improves prediction accuracy but also enhances interpretability by highlighting which data sources are most influential in defect prediction under different conditions.

While the results are promising, several avenues remain for future research to build upon this foundation. First, expanding the framework to include additional sensor modalities—such as in-situ X-ray imaging, optical tomography, or real-time spectroscopy—could further enrich the data representation and enhance predictive robustness. Second, scaling the system for deployment in industrial environments with more complex part geometries, varied material systems, and diverse AM machines will be critical to validate its generalizability and practical utility [66]. Third, exploring transfer learning techniques could enable rapid adaptation of the model to new processes or materials with limited additional training data, reducing the barrier to adoption for smaller manufacturers.

Another important direction is the integration of uncertainty quantification within the predictive framework. Providing probabilistic confidence levels for defect predictions would be invaluable for risk assessment and decision-making in safety-critical applications [67]. Moreover, combining predictive quality control with downstream post-processing optimization—such as targeted heat treatments or surface finishing—could establish end-to-end manufacturing pipelines that ensure not only defect-free parts but also optimized mechanical and functional properties.

In conclusion, this paper presents a significant step forward in overcoming one of the most persistent challenges in metal additive manufacturing: the inconsistency in part quality due to unpredictable defect formation. By harnessing the power of multi-modal machine learning and hybrid deep learning architectures, the proposed real-time predictive quality control framework offers an effective and practical solution for early defect detection and process adaptation [68]. The demonstrated improvements in accuracy, reduction in false negatives, and enhancements in dimensional control highlight the transformative potential of this approach.

This research contributes not only to the scientific understanding of defect mechanisms in metal AM but also provides actionable tools that can be integrated into industrial manufacturing systems. The resultant gains in process reliability, cost efficiency, and material sustainability position metal additive manufacturing for broader adoption across high-value manufacturing sectors. Ultimately, the approach outlined here exemplifies the convergence of advanced sensor technologies, artificial intelligence, and manufacturing science—paving the way toward smarter, more adaptive, and highly reliable additive manufacturing processes in the near future. [69]

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