Integrating Deep Autoencoders and Bayesian Inference for Diagnostics and Health Management of Industrial Inkjet Systems

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ABSTRACT

Modern printing industry requires extreme reliability to achieve zero-defect production. This study contributes to the paradigm shift from reactive to predictive maintenance in industrial inkjet systems, reducing downtime, material waste, and operational costs. We present an integrated Diagnostics and Health Monitoring strategy leveraging piezoelectric self-sensing with deep autoencoders and Bayesian inference for real-time fault diagnostics. The system captures residual pressure waves in the ink chamber—exploiting the dual actuator-sensor function of piezoelectric crystals—as "acoustic signatures" to detect subtle nozzle deviations from clogging, air bubbles, or mechanical wear. Nozzle pressure signals feed into a multimodal autoencoder (AE) architecture, where each AE specializes in a distinct fault class (jetting, non-jetting, deviated, intermittent). AE outputs combine with Gaussian Mixture Models (GMM) and Bayesian inference to provide high-confidence classification, even with imbalanced industrial datasets. Tests on industrial printheads (Ricoh MH5420) demonstrate 99.4% accuracy in detecting critical failures and enabling preventive maintenance. However, while the system excels at detecting fluidic obstructions, challenges remain in classifying deviated and intermittent faults. The prognostic layer reuses the jetting autoencoder's reconstruction error (RE) as a continuous Health Indicator, correlating pressure-induced degradation with nozzle health. Controlled experiments varying ink chamber pressure reveal a parabolic RE-pressure relationship, with minimum RE at nominal operating range. This enables early degradation detection, as RE increases progressively before functional failure, supporting condition-based maintenance strategies.

1. INTRODUCTION: THE PARADIGM SHIFT IN INKJET QUALITY CONTROL

Industrial inkjet technology is widely used in industrial applications and is rapidly evolving from paper-based communication to complex functional applications like 3D printing, printed electronics, and sensor manufacturing. These processes utilize thousands of microscopic nozzles operating at high frequencies, where even a single failure—such as a clog, air bubble entrapment, or nozzle plate wetting—can cause quality defects. Traditional quality control relies heavily on post-process optical inspection, which is time consuming, inherently reactive and, being unable to predict faults, fails to prevent waste during high-speed production runs. Diagnostic methods for industrial inkjet systems have evolved from simple fault detection to predictive optimization. Early self-sensing approaches relied on piezoelectric signal monitoring to detect jet failures and air bubble entrapment (Kwon et al., 2013). While effective for multi-nozzle arrays, these methods provide binary fault indicators without process optimization capabilities. Recent data-driven approaches have demonstrated more sophisticated diagnostic capabilities. (Maffioletti, 2019) employed machine learning for real-time nozzle health estimation and failure prediction, achieving 5-10% maintenance cost reduction through autoregressive cleaning strategies. More recently, regression and classification models have been developed to predict jetting behavior from ink and printer parameters, explicitly targeting failure modes including no ejection, satellite drops, and nozzle clogging (Brishty et al., 2022). These predictive models enable upstream process optimization before physical printing trials, representing a paradigm shift from reactive fault detection to proactive process control. This study addresses this critical industrial need by investigating machine learning models capable of analyzing the electromechanical signals generated during the jetting cycle. The goal is to move beyond simple binary 'pass/fail' tests and develop a system capable of estimating the health status of nozzles in real-time, directly within the fluidic system, by tracking subtle degradation trends. This approach is consistent with the goals of 'Zero-Defect Manufacturing,' where computational intelligence is integrated with material science standards, such as the ISO 12647-2 framework (ISO, 2013), to ensure consistent output quality. The ability to predict and prevent nozzle failures before they occur can significantly reduce downtime,

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improve product quality, lower maintenance costs, and reduce the waste of materials and ink. One of the most critical challenges in inkjet printing is the loss of one or more nozzles during printing (non-jetting failure), which leads to visible defects and rejected products

This research presents an integrated diagnostics and health management architecture designed to address these issues. The system leverages piezoelectric self-sensing to capture pressure wave signatures and combines:

- A diagnostic module based on a framework of competing autoencoders and Bayesian inference for real-time fault detection and classification.
- A prognostic module exploiting the reconstruction error of the nominal autoencoder as a continuous Health Indicator (HI) that correlates with nozzle degradation

This approach enables a shift from reactive to predictive maintenance and offers operators actionable information about the current and estimated near-future state of the digital printing system.

2. THEORETICAL FRAMEWORK: PIEZOELECTRIC SELF-SENSING

The foundation of the proposed system is the exploitation of the reverse piezoelectric effect. The piezoelectric self-sensing technique (Bullot et al., 2024) (Wang et al., 2020) exploits the inherent properties of piezoelectric materials to both actuate and sense the state of the nozzle. As shown in Figure 1, the piezoelectric actuator (top) deforms in response to electrical voltage, creating pressure waves that eject ink droplets through the nozzle (bottom). During the refill phase, the same piezoelectric element acts as a sensor, detecting acoustic feedback and residual vibrations within the ink chamber. This dual functionality allows for a compact and efficient design, as no additional sensors are required. In a standard Drop-on-Demand (DoD) printhead, a piezoelectric crystal is deformed by a voltage pulse to create a pressure wave that expels a droplet. Following the ejection, residual pressure waves continue to vibrate within the ink chamber until they are damped by viscous dissipation.

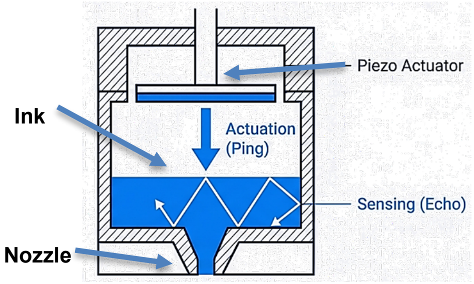

Figure 1 Piezoelectric self-sensing mechanism in inkjet printhead technology.

Because the crystal remains mechanically coupled to the fluid, these vibrations induce a measurable electrical voltage on the actuator electrodes.

This "echo" signal constitutes a unique signature of the nozzle's internal state. As shown in Figure 2 healthy nozzle produces a consistent, damped sinusoidal response, while an obstructed nozzle or one containing air bubbles will exhibit a drastically different frequency and amplitude profile. By capturing these impulse responses, the system gains access to a wealth of diagnostic data without the need for additional external sensors, making it a cost-effective and low-invasive solution for industrial environments.

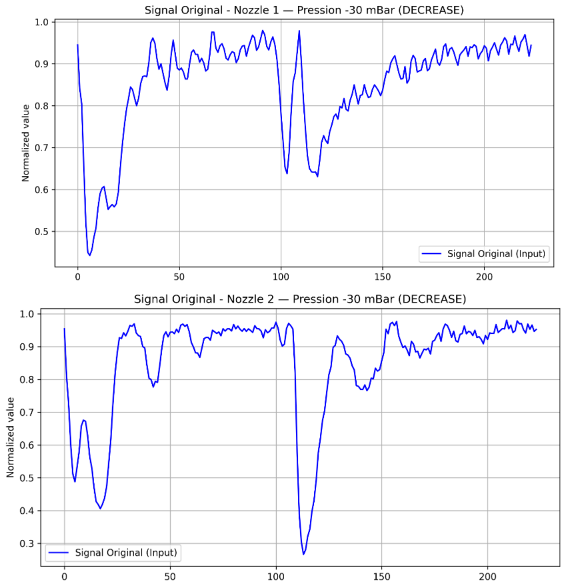

Figure 2. Echo signals: Faulty nozzle top. Healthy nozzle bottom. X-axis sample number

3. STATE OF THE ART

Autoencoder-based prognostics have demonstrated substantial capabilities across diverse industrial systems, including aviation turbofan engines, mechanical bearings, HVAC systems, wind turbines, and lithium-ion batteries (Cheng et al., 2022; de Pater & Mitici, 2023; Hasani et al., 2017; He et al., 2022; Tian et al., 2023). Studies consistently highlight three key advantages of autoencoders: the ability to handle unlabeled or limited labeled data through unsupervised or semi-supervised training, robust feature extraction from high-dimensional sensor data, and adaptability to varying operating conditions. These advantages translate into improved performance results, such as enhanced health indicator monotonicity and higher F1 scores for fault classification.

To our knowledge, no previous studies have specifically addressed printhead prognostics using autoencoders, representing a significant gap in the literature. However, the successful application of autoencoder approaches in aviation, mechanical systems, and building systems suggests technical feasibility for printhead applications. The work conducted within the InnoSuisse project 104.897 IP-ENG (Filliger et al., 2023) , has enabled the creation of a unique labelled database which has been exploited in this research. Such database includes test pattern images combined to acoustic recordings of nozzle post-jetting pressure oscillations (Figure 3), providing a comprehensive set of printing defects.

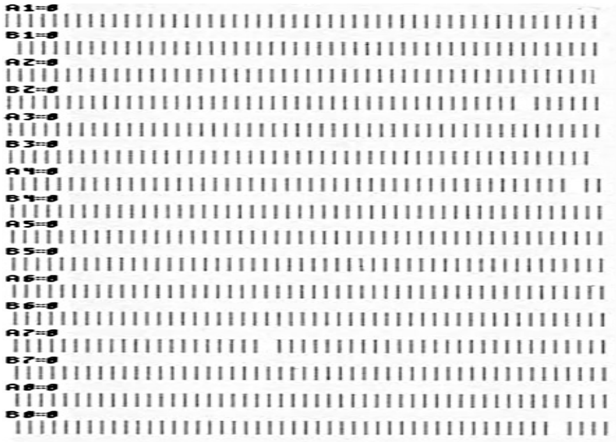

Figure 3. Test pattern image showing printed line segments (one per nozzle) used for ground-truth label generation.

The supervised training of diagnostic autoencoders requires labeled acoustic signal data. Our labeling methodology exploits the simultaneous acquisition of two complementary data streams during test print runs:

1) piezoelectric acoustic signals recorded from each nozzle during jetting cycles for test image production
2) printed test patterns where each nozzle deposits a discrete line segment on the substrate.

During test printing, each nozzle prints a visible line segment while its piezoelectric element simultaneously records the acoustic pressure wave signature of that specific jetting event. This creates a one-to-one correspondence between printed output and acoustic signal.
Computer vision algorithms (Duc, 2023; Rossy, 2023) analyze the morphological characteristics of each printed line segment, including continuity, straightness, presence of satellite drops, missing segments, and directional accuracy. Figure **3** shows a representative test pattern where visual inspection reveals the quality variation across nozzles.
Based on quantitative image features, the algorithm automatically classifies each line segment and assigns the corresponding health status label to the nozzle:

- Jetting: Continuous, straight line with no defects
- Non-jetting: Missing or completely absent line segment
-Deviated: Line displaced from expected position or showing directional anomalies
- Intermittent: Discontinuous line or irregular droplet pattern

Since each printed line corresponds to a specific nozzle and jetting event, the assigned label is directly associated with the piezoelectric acoustic signal recorded during that same cycle. This creates a labeled dataset where ground truth is derived from actual print quality the ultimate metric of industrial relevance.
This automated pipeline processes thousands of nozzles across multiple print runs, generating a large-scale labeled dataset (>500,000 samples) suitable for deep learning model training without manual annotation. This approach provides objective, repeatable ground-truth labels while avoiding subjective interpretation of acoustic signals. Importantly, the labels reflect functional performance (print quality) rather than arbitrary signal features, ensuring that the diagnostic models are trained to predict outcomes that matter for production quality.

4. ARCHITECTURE OF THE SYSTEM

The system is designed to provide anomaly detection and fault diagnostics and health monitoring through a multi-layered computational pipeline. The system uses piezoelectric signals as input and outputs both fault classification and health state monitoring. Figure 4 shows the algorithmic architecture with the diagnostic layer (multi-model autoencoders) and prognostic layer (nominal autoencoder) working in tandem.

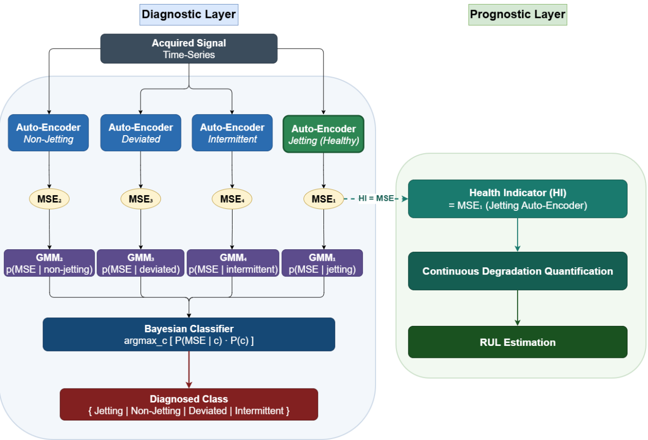

Figure 4: Algorithmic Architecture

The diagnostic layer employs a competitive framework of specialized autoencoder, each trained on a specific fault class (Jetting, Non-jetting, Deviated, Intermittent)

The prognostic layer exploits the reconstruction error of the same "jetting" autoencoder used in the classification as a continuous metric of nozzle health. It represents the Health Indicator (HI): which serves to give predictive insights.

The system pipeline has 3 main steps:

1) Piezoelectric signals are acquired and preprocessed
2) Diagnostic layer classifies current nozzle state
3) Prognostic layer analyzes HI trends over time

The integration mechanism combines the two outputs to trigger maintenance alerts or initiate corrective actions, such as software-based compensation, automated cleaning cycles, or even stop the printing process when major failures are detected, thereby achieving virtually waste-free production.

5. EXPERIMENTAL SETUP

In this study we used the MH5420 industrial inkjet printhead (manufactured by Ricoh, Japan), which has 1,280 nozzles configured in 4 banks. This printhead has been used because of the ability to measure the piezo response directly through the electronic drivers used to control the piezo actuators (Figure 5). The experimental setup involved capturing signals from a wide range of nozzles under various operating conditions. This diversity in the dataset ensures that the model is robust and generalizable to different scenarios encountered in industrial settings. A full printhead data set consists of acoustic recordings from 1280 nozzles. Two printhead datasets are acquired per minute. The pressure signal inside the nozzle is measured at a sampling rate of 2 MHz. Each nozzle raw signal consists of a raw time series of 256 samples spanning about 128µs.

Our diagnostics dataset contains more than 500,000 echo signals labelled through image processing techniques as:

- Jetting: Healthy operation; correct ink droplet ejection.
- Non-jetting: Complete blockage; no droplet ejection.
- Deviated: Jet direction anomaly; droplet misplacement.
- Spray/Intermittent: Unstable operation; random droplet ejection.

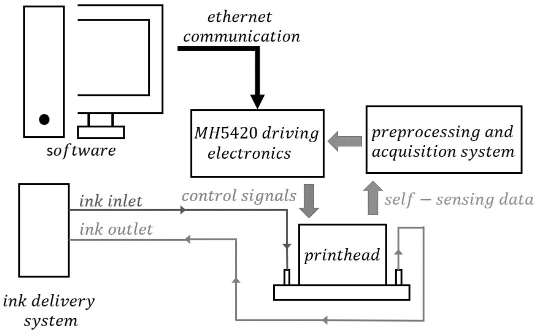

Figure 5. Block diagram of the measurement setup

6. DATA PRE-PROCESSING AND FEATURE ENGINEERING

The research evaluated two distinct formats of input data for the autoencoders: raw temporal signals consisting of 256 points, and pre-processed feature vectors containing spectral descriptors like frequency peaks, energy, amplitude, phase, and damping coefficients (14 elements). In both cases initial data preparation involves a "signed normalization" step, scaling values between -1 and 1 to preserve signal polarity, which is essential for the hyperbolic tangent (tanh) activation functions used in the neural layers.

7. THE DIAGNOSTIC LAYER: COMPETITIVE MULTIMODEL FRAMEWORK

7.1. Autoencoders

Autoencoders are neural networks trained to reconstruct their input signals.(Mienye & Swart, 2025) Their architecture (see Figure 6) can be subdivided into:

- Encoder: Compresses input signals into a latent space.
- Bottleneck: Captures essential signal features. The bottleneck layer represents the compressed signal.
- Decoder: Reconstructs the signal from the latent representation.

An autoencoder is designed to project input data into a compressed latent space and then reconstruct the original input as accurately as possible. After the operation, the system calculates the reconstruction error (RE) between the input signal and its output. Their main use for diagnostics is for fault/anomaly detection (Neloy & Turgeon, 2024)

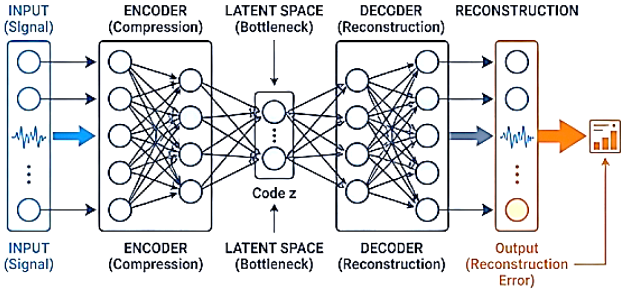

Figure 6.Autoencoder structure

7.2. Multimodel Framework

In this research, our goal is not to produce a rigid, binary classification but rather to derive a continuous measure of the likelihood that a nozzle belongs to each healthy or faulty class. To accomplish this, we exploited the autoencoder's reconstruction error as a key metric. While autoencoders are traditionally associated with anomaly detection, their ability to quantify deviations from nominal behavior makes them equally valuable for classification tasks, where understanding the degree of membership to each class is valuable for predictive maintenance. As a consequence, the system adopts a multi-model autoencoder competitive framework.

A dedicated autoencoder is trained for each nozzle state: Jetting, Non-jetting, Deviated and Intermittent. The reconstruction error of autoencoder trained for the jetting class (nominal) will be then also used in the prognostics layer. To dimension the "bottleneck" of the autoencoders, Principal Component Analysis (PCA) has been employed as a methodological tool to estimate the intrinsic dimensionality of the signals. This ensures the latent space is narrow enough to force the model to learn only the most essential structural correlations, effectively filtering out noise. Jetting and non-jetting autoencoders have been trained with 180000 examples each, whilst classes Deviated and Intermittent with 20000 signals each. Autoencoder structure is presented in Table 1

Autoencoders were trained using both pre-processed feature vectors and raw time-series data. Since the raw time-series approach yielded higher accuracy, the remainder of this document focuses on the results and analysis derived from this input method.

Table 1: Raw Data Autoencoder Architecture Details

Layer	Description
Input	Raw (256 time-domain points)
Encoder	3 fully connected layers (128, 64, 32 neurons); tanh activation.
Bottleneck	10 neurons; linear activation.
Decoder	3 fully connected layers (32, 64, 128 neurons); tanh activation
Output	Reconstructed signal; Mean Squared Error (MSE) as loss function.

7.3. Bayesian Classifier

For the diagnostic task, the reconstruction errors of the training dataset are first computed for all four autoencoders, each one representing a specific nozzle status class (jetting, non-jetting, deviated, intermittent). These reconstruction errors constitute the statistical features used for classification. To model the statistical behavior of these errors, a Gaussian Mixture Model (GMM) is fitted for each combination of autoencoder j and nozzle status class C_k. In other words, for each class C_k, the distribution of reconstruction errors MSE_j produced by autoencoder j is modeled using a GMM. This procedure provides an estimate of the class-conditional likelihood:

$$p(MSE_j|C_k) \tag{1}$$

that is, the probability density of observing a given reconstruction error MSE_j from autoencoder $\boldsymbol{j}$, assuming that the true nozzle status is $\boldsymbol{C_k}$.

The purpose of modeling the reconstruction error distributions through GMMs is to enable probabilistic interpretation during testing. Specifically, when a new signal is acquired, it is simultaneously processed by all trained autoencoders. Each autoencoder produces a reconstruction error, which is then evaluated under the corresponding GMM models to compute the likelihoods $p(MSE_j|C_k)$ for all classes.

This step is essential because the Bayesian classifier relies on the assumption that the reconstruction errors associated with each nozzle status class follow a probability distribution that can be appropriately modeled. By capturing these distributions through GMMs, the system accounts for statistical variability and potential overlap between classes.

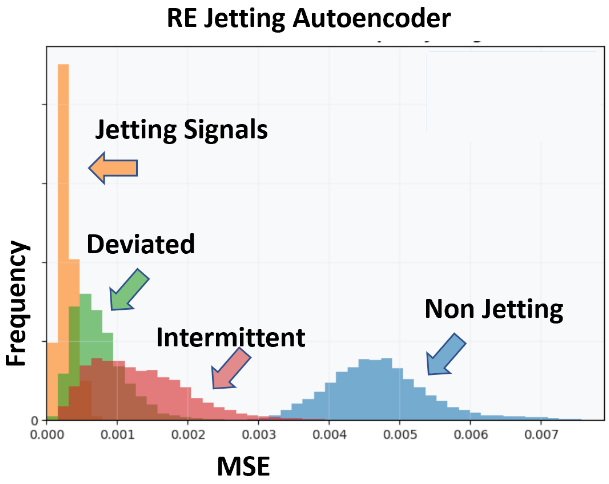

Figure 7. Reconstruction error distribution of the Jetting Autoencoder for the different classes on training set

The resulting likelihoods are then combined within the Bayesian decision framework to estimate the posterior probabilities $P(C_k|D)$ where $D = \{MSE_1 \dots MSE_N\}$ represents the set of observed reconstruction errors.

$$P(C_k|MSE_k) = \frac{p(MSE_k|C_k) \cdot P(C_k)}{\sum_{j=1}^{N} p(MSE_k|C_j) \cdot P(C_j)} \tag{2}$$

Where $p(MSE_k|C_k)$ are the likelihoods from GMM and $P(C_k)$ is the prior probability of the class C_k, N is the number of the classes.

This probabilistic formulation enables robust classification based on how well the observed error pattern matches the learned statistical models of each nozzle condition.

Overall, the integration of autoencoder-based feature extraction with GMM-based likelihood modeling provides a principled probabilistic foundation for nozzle status diagnosis, allowing reconstruction errors to be interpreted not merely as anomaly scores but as statistically grounded indicators of class membership.

Finally the classifier assigns the class with the highest posterior probability. This strategy allows the system to make high-confidence decisions even in the presence of industrial data imbalances.

7.4 Diagnostic Classification Results

The system achieves 99.4% accuracy in detecting non-jetting faults. However, deviated and intermittent faults are harder to distinguish from healthy operation due to similar pressure wave signatures.

7.4.1 Performance analysis by fault class

The diagnostic and classification performance of the PHM system was evaluated for each fault class: The results, summarized in Table 2, reveal significant variations in performance across the different classes. Below, we discuss the specific characteristics and challenges associated with each class.

Table 2: Classification Performance Metrics by Fault Class

Fault Class	Accuracy (%)	Precision	Recall	F1-Score
Jetting	98.6	0.98	0.99	0.98
Non-jetting	99.4	0.99	0.98	0.99
Deviated	73.4	0.72	0.75	0.73
Intermittent	61.2	0.60	0.62	0.61

The jetting class, representing healthy nozzles, achieved the highest classification accuracy (98.6%). This high performance is attributed to the distinct and consistent pressure wave patterns generated by healthy nozzles. The autoencoder trained on the jetting class effectively learned the characteristic features of these signals, resulting in low reconstruction errors for healthy nozzles and high errors for faulty ones. The confusion matrix (Table 3) shows minimal misclassification, with most errors occurring at the boundary between jetting and deviated classes resulting in a low false alarm rate.

The “non-jetting” class, representing completely blocked nozzles, also achieved high classification accuracy (99.4%). Non-jetting nozzles produce flat or highly distorted pressure wave signals, which are easily distinguishable from healthy signals. The autoencoder trained on this class effectively captured these distinct patterns, resulting in high reconstruction errors for non-jetting signals and low errors for healthy signals. The confusion matrix (Table 3) confirms the robustness of the classification, with almost no misclassification.

The “deviated” class, representing nozzles with misdirected ink jets, presented significant classification challenges, achieving only 73.4% accuracy. The primary difficulty arises from the similarity between deviated and jetting pressure wave signals. Unlike other fault classes, the error for deviated nozzles does not appear always linked to pressure variations in the nozzle chamber but it seems associated with electronic factors. As a consequence, deviated nozzles often produce signals that closely resemble those of healthy nozzles, making it difficult for the autoencoder to distinguish between the two classes. The confusion matrix (Table 3) shows a high rate of misclassification between deviated and jetting classes, indicating the need for improved feature extraction or additional sensor data to address this limitation.

The “intermittent” class, representing nozzles with unstable ink ejection, achieved the lowest classification accuracy (61.2%). This poor performance is due to the high variability in pressure wave signals produced by intermittent nozzles. These signals can fluctuate between healthy and faulty patterns, making it challenging for the autoencoder to learn a consistent representation. The confusion matrix (Table 3) shows substantial misclassification across all classes, highlighting the need for more sophisticated classification techniques or additional data sources.

Table 3: Classification Confusion Matrix

True\Predicted	**Jetting**	**Non-Jetting**	**Deviated**	**Intermittent**
Jetting	99	0	1	0
Non-Jetting	0	99	0	1
Deviated	24	0	73	3
Intermittent	20	4	15	61

Interestingly, the research found that defects like "Deviated" or "Intermittent" jets show consistent signatures across all pressure ranges. This implies these defects are often caused by external mechanical factors—such as dirt on the nozzle plate or electronics—that do not fundamentally alter the internal pressure wave. Consequently, while the piezoelectric system excels at fluidic health monitoring, it reaches its limits in detecting purely trajectory-based defects.

8. THE PROGNOSTICS LAYER: MSE AS A PREDICTIVE METRIC

The prognostic layer exploits the reconstruction error (MSE) from the nominal (jetting) autoencoder as a Health Indicator (HI), providing a continuous measure of nozzle health and degradation trends. This metric offers several advantages over binary classification: continuous health monitoring, sensitivity to subtle signal changes before functional failure, and direct correlation with physical degradation processes.

Because the jetting autoencoder has learned only the features of healthy nozzles, any deviation from optimal operation whether from clogging, pressure drift, or mechanical wear results in increased reconstruction error. This progressive increase enables early detection of degradation before complete failure, supporting predictive maintenance strategies.

8.1. Prognostics validation

To validate the prognostic capabilities of the MSE-based health indicator, we conducted controlled experiments by systematically varying the ink chamber pressure from -70 mBar to -20 mBar while monitoring 1,280 nozzles on a Ricoh MH5420 printhead. The nozzle class distribution as a function of pressure reveals that the "non-jetting" condition becomes dominant outside the stable operating window (approximately -40 to -60 mBar), while the "jetting" state prevails within this optimal range. Based on the observed MSE-pressure relationship, we established three operational zones:

- Healthy Zone (Green): MSE < 0.0006: Optimal operation (-40 to -60 mBar), stable jetting with no intervention required.
- Warning Zone (Yellow): 0.0006 ≤ MSE < 0.0007: Early degradation detected (-60 to -65 mBar and -40 to -30 mBar), monitoring intensified.
- Critical Zone (Red): MSE ≥ 0.0007 — Advanced degradation (< -65 or > -30 mBar), maintenance recommended.

Figure 8 illustrates the evolution of average reconstruction error as a function of pressure. The parabolic trend clearly shows that MSE increases progressively as pressure deviates from the optimal range, providing a quantitative indicator of degradation severity. Points where the majority of nozzles maintain jetting status are represented in circles, while points dominated by non-jetting failures are shown in squares.

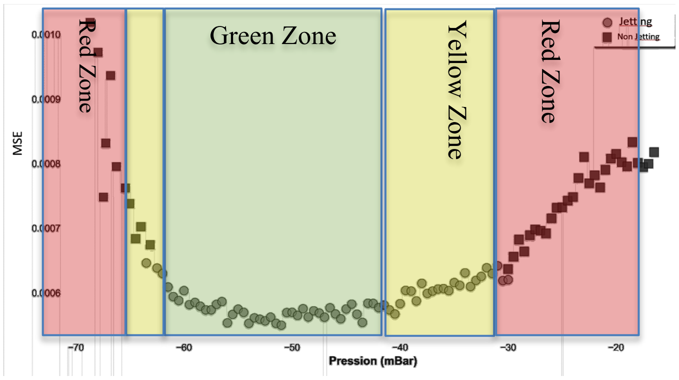

Figure 8 Evolution of the average (1280 nozzles) reconstruction error as a function of pressure.

Additionally, we operated nozzles under constant sub-optimal pressures (below -60 mBar and above -40 mBar) until non-jetting failure to establish a quantitative pressure-deviation-to-failure relationship.

To evaluate the prognostic capabilities beyond qualitative observations, we quantified the MSE-based Health Indicator performance using Prognostic Horizon metric to assess the system's ability to provide advance warning of nozzle degradation with measurable confidence.

8.2.1. Prognostic Horizon

The Prognostic Horizon (PH) quantifies the time-to-failure by measuring the elapsed time between early warning detection (MSE entering the Warning Zone at 0.0006) and actual functional failure (transition to non-jetting state). In these run-to-failure experiments conducted at typical industrial print speeds (20 kHz), we observed:

- Average PH: ~3 minutes between warning threshold crossing and non-jetting failure
- Minimum PH: ~1 minute (rapid degradation under severe pressure deviation)
- Maximum PH: ~8 minutes (gradual degradation under moderate pressure deviation)

This advance warning window provides sufficient time for corrective actions such as printhead cleaning, pressure adjustment, or controlled production shutdown. These results demonstrate that the MSE-based Health Indicator provides measurable prognostic capabilities, potentially enabling predictive maintenance strategies. However, several limitations must be acknowledged. The current prognostic approach is primarily sensitive to faults that affect pressure wave signatures. Failure modes such as "deviated" or "intermittent" jets, which may not significantly alter the acoustic signal pattern, present challenges for MSE-based degradation level assessment and require complementary diagnostic modalities for comprehensive health monitoring. Moreover, before implementing predictive maintenance strategies in production environments, it is necessary to validate these findings across multiple MH5420 printheads to demonstrate repeatability and robustness.

9.1. Challenges and Limitations

While the system demonstrates strong performance in detecting major faults (jetting and non-jetting), several challenges and limitations were identified during the classification of subtle faults (deviated and intermittent).

The pressure wave signals for deviated and intermittent nozzles often resemble those of healthy nozzles, leading to high misclassification rates. This similarity suggests that the piezoelectric sensors used may not provide sufficient information to distinguish between subtle faults. Integrating additional sensors, such as optical sensors, could improve classification accuracy

The dataset contained a significantly higher number of samples for the jetting and non-jetting classes compared to the deviated and intermittent classes. Despite the Bayesian inference logic this imbalance may have biased the classification towards the majority classes, reducing their ability to recognize to the minority classes.

9.2. Implications for Industrial Applications

The diagnostic and classification results provide important insights into the industrial applicability of the proposed framework for inkjet printhead monitoring.

The high classification accuracy achieved for the “jetting” and “non-jetting” classes demonstrates the robustness of the proposed approach in detecting complete nozzle blockages. From an industrial perspective, this capability is particularly relevant, as non-jetting faults represent the most disruptive failure mode in production environments. Accurate and timely detection enables rapid intervention, thereby reducing unplanned downtime, minimizing material waste, and lowering maintenance cost.

The comparatively lower performance observed for “deviated” and “intermittent” faults highlights current limitations in the system’s sensitivity to subtle degradation phenomena. These fault types often correspond to early-stage anomalies that may not significantly alter pressure wave signatures. Enhancing their detectability is crucial for advancing from fault detection toward fully predictive maintenance. Future work should therefore focus on improving feature representation, model generalization, and the integration of additional discriminative information.

The proposed system can already be embedded within existing printhead control systems to enable continuous, real-time health monitoring.

9.3. Future directions

The results presented in this study constitute a foundation for the development of a full-scale industrial predictive maintenance framework for inkjet printheads.

Future research will focus on extending the proposed methodology toward temporally aware and prognostic models capable of supporting Remaining Useful Life (RUL) estimation and long-term health forecasting.

A primary research direction concerns the modeling of time-dependent degradation phenomena. The current approach evaluates nozzle condition at a given operating state; however, nozzle “fatigue” is inherently dynamic. The integration of advanced temporal architectures—such as Variational Autoencoders (VAEs) or Recurrent Neural Networks (RNNs)—would enable the capture of sequential dependencies and progressive degradation patterns. Such developments are essential for. In addition, several methodological improvements are envisaged:

- Address class imbalance through synthetic data generation or targeted augmentation strategies to strengthen model generalization and improve detection performance for minority fault categories.

- Integrate additional sensing modalities to provide complementary information to pressure wave analysis, thereby improving fault discrimination and early anomaly detection.

Overall, these research directions aim to evolve the current framework into a comprehensive, prognostic, and industrially deployable solution capable of delivering measurable operational and economic benefits.

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