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## Research Article

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# G-codes-coupled wireless vibration trajectory-based side-channel monitoring for raster-angle intrusion detection in fused filament fabrication

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## Abstract

Cyber-physical intrusions in fused filament fabrication (FFF) can alter raster orientation and compromise the internal structure and mechanical integrity of printed components without producing readily observable changes in external geometry, creating an integrity concern for mechanically mission-critical components. This vulnerability motivates independent side-channel monitoring to detect unauthorized raster-angle alterations by linking digital manufacturing commands with measured physical responses. This study presents a wireless vibration- and G-code trajectory-informed side-channel monitoring framework for identifying closely spaced raster-angle states in FFF using ASTM-standard dogbone specimens. Four distributed tri-axial accelerometer nodes wirelessly transmit vibration measurements to an external server without modifying or accessing the printer controller. Experiments comprise 70 independently printed specimens representing seven raster angles from 45° to 75° at 5° increments. The proposed pipeline integrates G-code trajectory descriptors with time-domain, directional, and wavelet-packet transform (WPT) vibration features, applies minimum redundancy maximum relevance (mRMR) feature selection, and performs classification using a Bayesian-optimized Gaussian support vector machine. As a benchmark, a vibration-only WPT-PCA pipeline uses principal component analysis (PCA) for feature reduction and the same classifier family. Across five repeated specimen-level evaluations, with all test-specimen observations excluded from model development, the proposed method achieved 100% test accuracy in every run, whereas the vibration-only benchmark achieved 90.00% mean accuracy with a 7.32% standard deviation. These results demonstrate that wireless vibration side channels can distinguish closely spaced raster-angle states, supporting raster-angle intrusion monitoring and future command-execution verification of mechanically mission-critical FFF components.

**Keywords:** Bayesian optimization, G-code, Minimum redundancy maximum relevance, Wavelet packet transform, Wireless vibration sensing.

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# 1 Introduction

## 1.1 Background

Fused deposition modeling (FDM), also known as fused filament fabrication (FFF), is a filament-based additive manufacturing (AM) process capable of producing complex and customized components directly from digital models through layer-by-layer deposition. The quality of AM-fabricated parts depends on the coordinated behavior of the filament, nozzle, thermal system, motion axes, print bed, toolpath, and operating environment. However, successful print completion does not necessarily indicate a defect-free part, as physical process deviations may occur without triggering machine errors. This distinction becomes particularly important when AM is viewed as a cyber-physical system (CPS), where digital instructions and physical manufacturing processes are tightly interconnected [1–4]. AM part fabrication involves multiple interconnected cyber-physical stages, including CAD modeling, geometry tessellation, slicing, G-code generation, data transfer, machine configuration, and physical fabrication, which is demonstrated in Fig. 1. Accidental configuration changes or deliberate cyber intrusions at any stage can alter part geometry, internal structure, process parameters, or mechanical performance. While some alterations may be visually detectable, others can remain hidden within the fabricated part without significantly changing its external appearance. Therefore, verification of the digital file alone cannot ensure that the physical fabrication process was executed as intended [5–10]. Side-channel monitoring provides an effective means of observing the physical execution of AM processes. Various sensing modalities, including cameras, thermal imagers, laser scanners, acoustic-emission sensors, microphones, accelerometers, force sensors, and motor-current measurements, have been investigated for real-time monitoring of material-extrusion processes [1–4,11,12]. Among these sensing modalities, vibration and acoustic sensing provide a complementary view because they do not require an unobstructed image of the deposited surface. These measurements respond to motor excitation, belt transmission, axis acceleration, carriage movement, nozzle condition, print-bed dynamics, structural resonances, and changes in the commanded trajectory. Previous studies have used accelerometers and acoustic-emission sensors to diagnose loosened components, nozzle blockage, filament

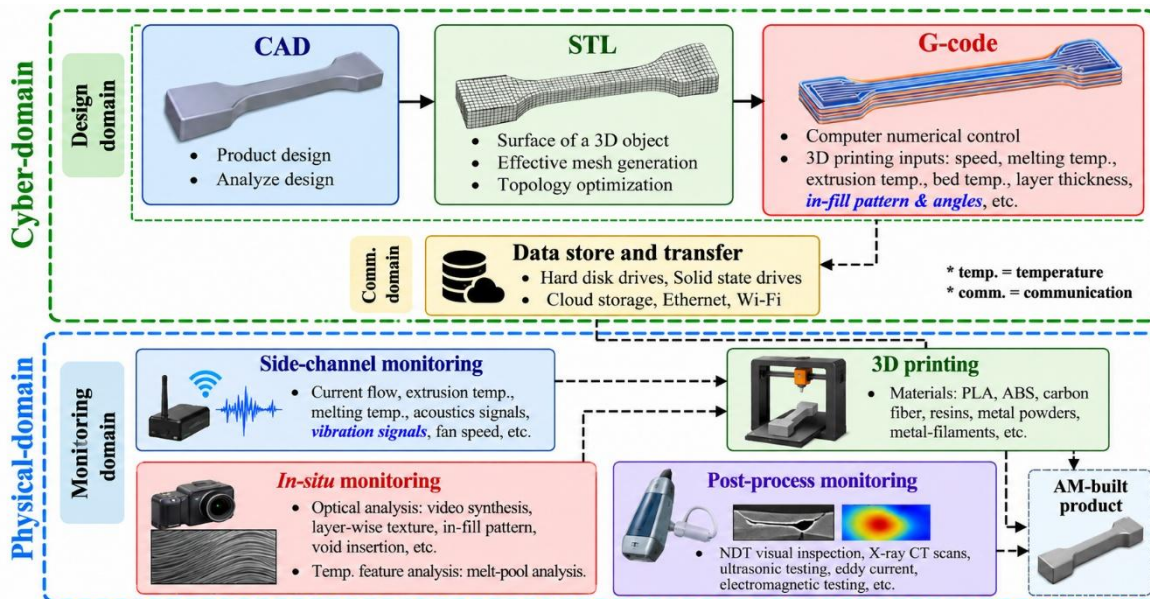


Fig. 1 Cyber-physical domain thread of AM systems and monitoring framework.

breakage, material depletion, warping, extrusion abnormalities, and other printing failures [13–22]. Signals from these sensors can reveal information about the motion of a printer, including the active axis, movement direction, and portions of the commanded geometry. Several cybersecurity studies have demonstrated that these side channels can be used to reconstruct toolpath information or detect unauthorized process changes [23–29]. In other words, side-channel observability is double-edged. It can create confidentiality risk, but it can also provide an independent source of evidence for process integrity monitoring. Wireless sensing is attractive in this setting. It allows a monitoring layer to be added without modifying the printer’s internal controller. A sensing edge acquires the physical response, transmits it to an external server, and preserves a logical separation between the system generating the command and the system evaluating its execution. Cloud-connected manufacturing platforms and digital twin studies have already demonstrated the value of remote data acquisition and real time quality assessment and monitoring in additive manufacturing [30–33]. The remaining challenge is determining whether a low-cost wireless sensing module can differentiate manufacturing stages that are physically similar rather than only detecting large or visually obvious failures. Raster angle is a useful cyber-physical test case because it is simultaneously encoded in G-code, expressed through coordinated X-Y motion and embodied in the printed part, where it affects bonding, load transfer, anisotropy, strength and deformation [34–36]. Changes in raster angles alter the relative participation of the motion axes and can produce measurable tri-axial vibration differences. However, neighboring angles are difficult to distinguish because most printing movements remain similar, while build variation, sensor mounting, and environmental noise further increase signal overlapping. Previous studies have primarily treated raster angles as a predefined design parameter and investigated their alteration through G-code trajectory analysis derived from layer-wise images [37,38]. Also, the studies have not combined distributed wireless vibration sensing, specimen-independent testing, and separate evaluation of digital-command and vibration-only evidence. This separation is important because G-code features may accurately reveal the intended angle without confirming its physical execution, while fused results may obscure whether the classifier recognized the vibration response or merely decoded the command. Evaluation can also be inflated when segments from the same specimen appear in both training and testing or when preprocessing uses held-out data. Specimen-level partitioning and training-only normalization, feature reduction, and model optimization are therefore essential [39–44]. Fig. 2 illustrates this relationship using representative dogbone specimens with 45° and 75° raster orientations. Although the specimens share the same external geometry, their G-code-derived X- and Y-axis motion profiles and measured vibration responses exhibit visible differences. These examples motivate the central research question: Can wireless vibration measurements reliably distinguish closely spaced raster-angle states in previously unseen specimens, and how does incorporating commanded trajectory information affect identification performance?

## 1.2 Technical contributions

To address the research question of whether wireless vibration measurements can reliably distinguish closely spaced raster-angle states in previously unseen specimens and how commanded trajectory information influences identification performance, this study develops a wireless vibration- and trajectory-informed side-channel monitoring framework for raster-angle identification and intrusion detection. Fig. 3 illustrates representative raster-angle configurations, denoted A°, B°, C°, and D°. Multiple tri-axial accelerometers were used, each connected to an

individual microcontroller module. Sensing nodes were installed on the print-bed structure and positioned near the nozzle or printhead assembly. The nodes transmit batched measurements over Wi-Fi using HTTP POST requests with plain-text CSV-formatted payloads to a Flask-based server. This arrangement creates an external sensing pathway without altering the printer's internal motion-control system. Two complementary machine-learning pathways are evaluated. The trajectory-informed *wavelet packet transform (WPT)*–*mRMR*–*support vector machine (SVM)* pipeline combines G-code trajectory descriptors with time-domain, directional, and wavelet-packet vibration features. It represents the expected digital state together with its associated physical response. The directional-vibration WPT–PCA–SVM pipeline excludes G-code information and estimates raster angle exclusively from measured vibration. Reporting the pathways separately makes it possible to determine how much discrimination comes from deterministic command encoding and how much is supported by an independent physical side-channel. The dataset contains 70 independently printed specimens, with ten specimens representing each raster-angle class. Each specimen contributed four sensor-specific tri-axial vibration observations, one from each of the four sensing nodes, resulting in 280 observations. For each evaluation run, specimens were initially allocated at the class level to training, validation, and testing subsets. The training and validation subsets were subsequently combined into a 63-specimen development set, while seven specimens remained isolated for final testing. Five repeated specimen-level splits were used to assess sensitivity to the selected test specimens. Preprocessing, feature reduction, hyperparameter selection, and classifier development were performed using the combined development data, while the held-out test specimens remained excluded from model development. The main contributions of this study are as follows:

- **Retrofit wireless side-channel monitoring for AM intrusion detection:** A non-intrusive sensing architecture integrates four distributed wireless tri-axial accelerometer nodes with external server-based data acquisition, enabling physical side-channel monitoring and cyber-physical intrusion detection without modifying or accessing the AM machine controller.
- **Trajectory-informed detection of raster-angle intrusions:** Seven closely spaced raster-angle states at 5° increments are investigated as potential toolpath alterations. A trajectory-informed WPT–mRMR–SVM framework is benchmarked against a vibration-only directional WPT–PCA–SVM pipeline to assess whether coupling commanded tool motion with physical vibration signatures improves intrusion identification.
- **Specimen-independent validation of intrusion-detection reliability:** Specimen identity is preserved during data allocation, withheld-out specimens completely excluded from model development. Five held-out specimen runs, confusion matrices, and feature-space visualizations are used to evaluate the robustness and repeatability of side-channel-based intrusion detection beyond a single aggregate accuracy metric.

The objective of this work is to determine whether closely spaced raster-angle states can be distinguished using wireless vibration sensing and to quantify how commanded trajectory information influences classification performance. The study asks what information the classifier uses, whether that information comes from the commanded trajectory or the measured machine response, and whether the relationship transfers to previously unseen physical specimens. The remainder of the paper is organized as follows. Section 2 reviews material-extrusion monitoring, raster-angle research, vibration-feature representation, cyber-physical side channels, machine-learning leakage, and the identified research gaps. Section 3 presents the analytical methodology, including G-code trajectory

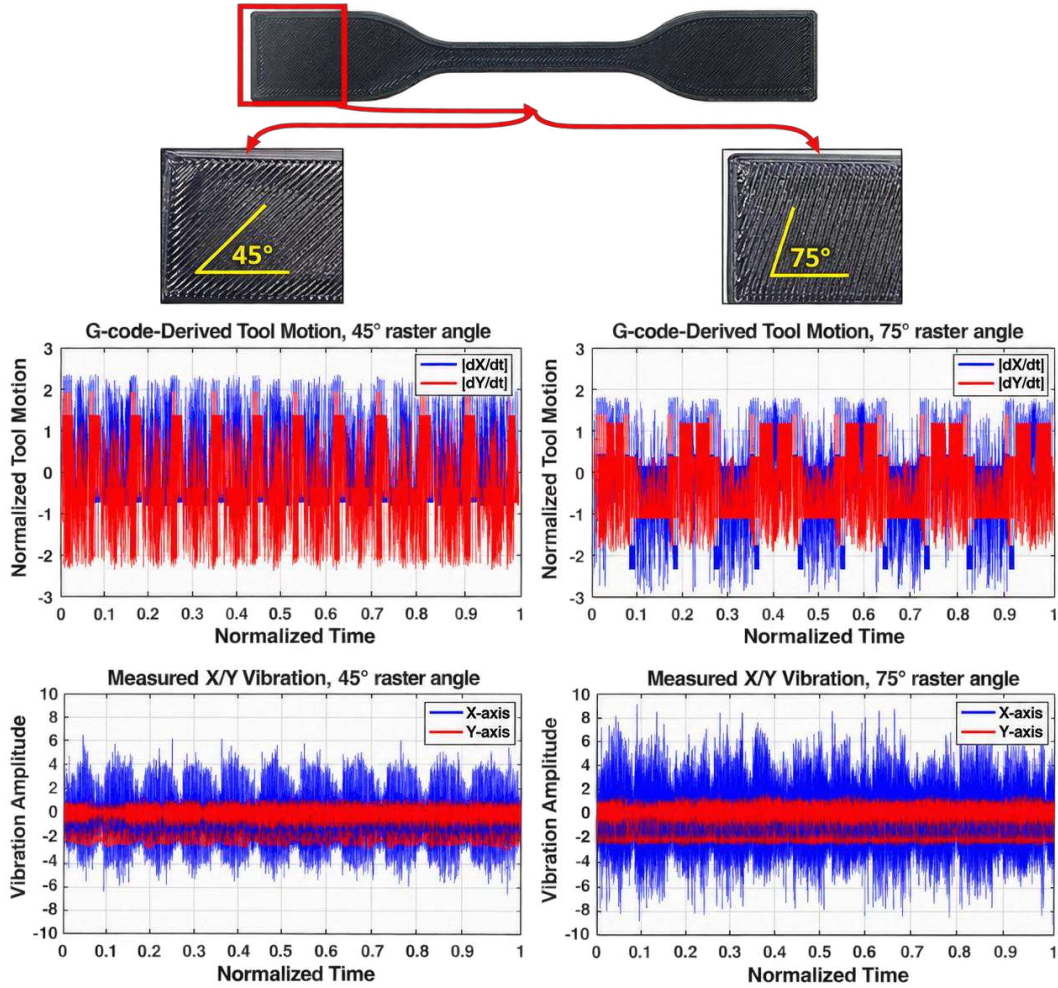


Fig. 2 3D-printed dogbone specimens with 45° and 75° raster orientations, showing corresponding G-code-derived tool motion and measured X/Y vibration responses. The comparison highlights motion and vibration differences despite identical external geometries.

formulation, vibration-signal processing, feature extraction, dimensionality reduction, and classification. Section 4 describes the experimental setup, wireless sensing architecture, G-code configuration, and specimen-aware dataset partitioning. Section 5 presents and discusses the classification results, physical interpretation, cyber-physical significance, and evaluation limitations. Finally, Section 6 summarizes the main conclusions and outlines directions for future research.

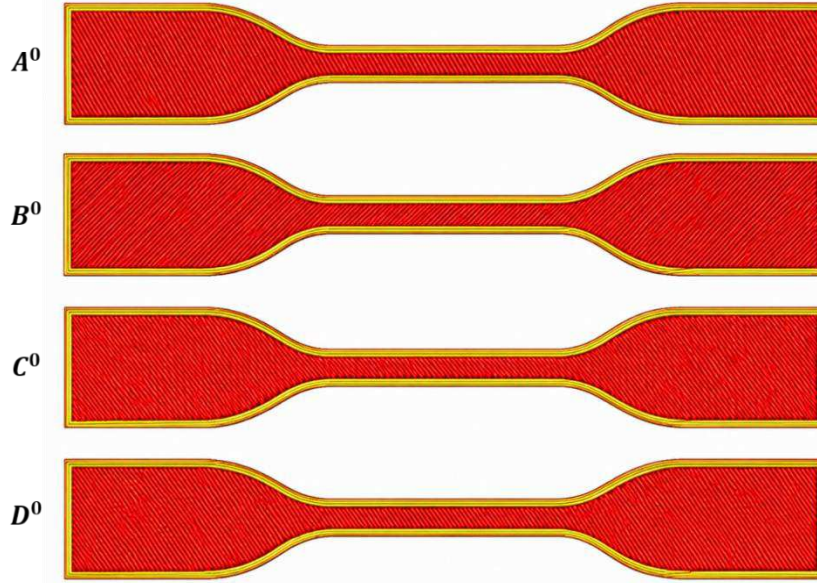


Fig. 3 G-code toolpath visualizations of material-extrusion dogbone specimens with different commanded raster-angle configurations.

## 2 Related work

### 2.1 *In-situ* monitoring of material-extrusion processes

Material extrusion-based printing is a digitally controlled process, but the physical quality of a model is affected by many interacting factors, including filament condition, nozzle temperature, extrusion rate, motion system behavior, environmental conditions and toolpath geometry. This combination makes process monitoring important for both quality assurance and cyber-physical security. Reviews of material-extrusion monitoring describe cameras, thermal sensors, laser scanners, acoustic-emission sensors, microphones, accelerometers, motor-current measurements, force sensors and multi-sensor systems as the main sensing approaches [1–4,12]. These modalities observe different aspects of the printing process. For example, cameras provide direct information about bead placement, surface appearance, under extrusion, layer shifting and geometric deviation. Holzmond and Li [11], demonstrated real-time defect detection using optical measurements of the deposited part. More broadly, image-based intelligent inspection systems can be affected by noise, illumination variation, occlusion, sensor limitations, and incomplete measurements, and structure-preserving reconstruction can improve the recovery of surface information for downstream quality assessment [45]. Thermal sensing provides a different view of the process. Combined infrared cameras and temperature sensors are commonly used to examine the cooling behavior, interlayer bonding, nozzle temperature and thermal gradients [2–4,11]. These measurements are valuable when the defect mechanism is strongly related to heat transfer, but it is comparatively expensive and their measurements may be influenced by different surface and environmental parameters. Acoustic and vibration sensing does not require direct observation of the deposited surface. Instead, these sensors respond to the dynamic behavior of the extrusion systems, motors, bearings, moving axes, print bed, frame and deposited material. Tlegenov et al. [20] attached an accelerometer to the extrusion system and showed

that vibration could be used to assess nozzle condition. Li et al. [21] developed a vibration-based framework for identifying normal and abnormal fused-filament-fabrication states using statistical features and support-vector-machine classifiers. Liu et al. [22] similarly demonstrated that acoustic-emission signals contain useful time- and frequency-domain information for diagnosing FDM process faults. These studies confirm that mechanical side-channel signals carry information about the state of the printer even when a defect is not directly visible. The strength of vibration sensing is also its main complication. An accelerometer does not respond to a single physical source. Its measurements contain contributions from axis motion, acceleration and deceleration, stepper-motor excitation, belt transmission, frame resonance, bed movement, extrusion events, and environmental disturbance. Sensor placement therefore has a considerable effect on the measured signal. A toolhead-mounted sensor is sensitive to local extrusion and carriage motion, whereas a bed- or frame-mounted sensor observes those events after they have passed through a different structural transfer path. Multi-sensor systems can improve observability, but they also increase synchronization, calibration, communication, and processing requirements [12,46]. Cloud-connected and digital-twin architectures have demonstrated how process measurements can be transferred from the printer to remote monitoring and decision systems [32,33]. Within such architecture, wireless accelerometer nodes offer a practical retrofit solution. The sensor, microcontroller and network interface can be attached without modifying the printer's internal controller or interrupting this motion control loop. Measurements can be transmitted in batches to a server for storage and analysis. Logical separation is particularly useful for integrity monitoring because the physical sensor does not depend entirely on the controller report that it is intended to verify.

## **2.2 Raster angle as a digital and physical process state**

Raster angle defines the orientation of the internal deposition lines relative to the specimen and printer coordinate systems. It is widely studied because it influences the load transfer, inter-bead bonding, tensile behavior and the anisotropy of a printed component [34]. From a monitoring perspective, however, raster angle is not only a material-structure parameter, but also a machine-motion state encoded in the G-code. Changing the raster angle changes the relative participation of the printer's X and Y axes. Because the stiffness, moving mass, belt behavior, and transfer path between each axis and an accelerometer are not identical, different raster directions can produce different vibration amplitudes, cross-axis relationships, and transient responses. This directional coupling provides the physical basis for estimating raster-angle state from tri-axial vibration. Previous research has applied machine learning to raster-angle-related problems, although with objectives different from physical side-channel verification. Ülkir et al. [37] evaluated regression algorithms for predicting a suitable raster angle from design and process-related data. Their random-forest model provided the strongest prediction among the evaluated algorithms. More directly related work was reported by Al Mamun et al. [38], who investigated raster-angle-based alterations as a cyber-physical anomaly. Their framework analyzed G-code trajectory distances and used a toolhead-mounted digital microscope to collect layer-wise images. Surface-texture features extracted from adaptive regions of interest were reduced using PCA and classified using multiclass SVM. This study established raster-angle alteration classification as a meaningful cyber-physical monitoring problem. Its physical evidence, however, was obtained from images rather than vibration.

### 2.3 Vibration representation, feature reduction and classification

Material-extrusion vibration is non-stationary because each printing segment contains deposition passes, reversals, acceleration, travel movements and transitions between infill and perimeter regions. Therefore, no single feature family can fully represent the process response. Time-domain features describe vibration magnitude and transient behavior through measures such as RMS, energy, peak to peak value, crest factor, skewness, kurtosis [21,22]. Directional features capture coordinated axis activity using cross axis correlations. RMS and energy ratios, orientation angles and statistics derived from the x-y vibration vector. Frequency domain features describe how vibration energy is distributed across frequency. Wavelet-packet transform (WPT) provides a multiresolution representation by decomposing the signal into structured frequency sub-bands. Sub-band energies and their ratios can therefore capture transient behavior while reducing sensitivity to differences in overall sensor amplitude [47,48]. Although time-domain, directional and WPT features provide complementary information, some are strongly correlated. Feature reduction is therefore required to control redundancy and model complexity. Minimum-redundancy maximum-relevance selection and principal component analysis provide two distinct approaches to feature reduction. mRMR is a supervised feature-selection method that uses mutual information to favor variables associated with the target class while penalizing redundancy among the selected variables [49]. Because it preserves the original predictors, the selected feature names remain physically interpretable. The resulting feature set can therefore indicate whether classification depends primarily on G-code trajectory descriptors, vibration magnitude, directional axis balance, transient indicators, or particular WPT sub-bands. PCA is unsupervised and instead constructs orthogonal linear combinations that explain the dominant variance in the standardized predictors [50]. It can reduce multicollinearity and suppress low-variance variation, but each principal component combines contributions from multiple original features. Consequently, the reduced representation is generally less interpretable in physical terms. Comparing mRMR and PCA is therefore more than a comparison of two dimensionality-reduction algorithms. It contrasts a label-informed, feature-preserving representation with an unsupervised latent representation. After feature reduction, support-vector machines provide a suitable classification framework for compact datasets with potentially nonlinear decision boundaries [51]. A Gaussian-kernel SVM is combined with error-correcting output codes for seven-class recognition, while Bayesian optimization is used to select the box constraint and kernel scale [52,53].

### 2.4 Cyber-physical integrity and machine learning leakage

The AM digital thread extends from CAD geometry through tessellation, slicing, G-code generation, file transfer, machine configuration and physical fabrication. A modification introduced at any of these stages can affect the printed component. Demonstrated threats include changes to geometry, internal structure, process parameters, orientation and machine instructions [5–7]. Some alterations may remain visually subtle while reducing the strength or intended functionality of the finished part. Physical side channels have a dual role in this setting. Acoustic and vibration emissions can reveal information about a printed object which creates a confidentiality risk. But at the same time the same signals can also provide evidence of unauthorized process changes. Yu et al. [23] showed that combining several physical side channels improved sabotage attack detection relative to individual sensing channels. Shi et al. [24] subsequently developed an online LSTM-autoencoder framework for detecting cyber-physical attacks from side-channel data. The release of synchronized audio and vibration datasets from modern cartesian and CoreXY printers

further demonstrates that printer motion is mainly observable through physical emissions, even when newer machines incorporate noise and vibration reduction mechanisms [25]. A central issue is the distinction between an expected command and its physical execution. If the target variable is raster angle, a G-code file sliced specifically for that angle will naturally contain different X and Y-axis trajectories. Statistics calculated from the same G-code can therefore provide a nearly direct representation of the class label. High accuracy from these variables demonstrates recognition of the intended command, but it does not independently prove that the printer executed that command correctly. This distinction is closely related to target leakage. Leakage occurs when information unavailable under the claimed inference setting enters model training or evaluation. It includes direct feature target encoding, non-independent training and test samples, and preprocessing fitted using evaluation data [39]. In the present application, G-code trajectory variables are not meaningless or invalid; they are valuable expected-state descriptors. The problem arises only when their classification accuracy is interpreted as independent evidence of physical execution. A second form of leakage can occur when segments from the same specimen appear in both training and testing. Those segments share material, machine condition, sensor mounting, environmental effects, and build-specific disturbances. A model may therefore recognize the specimen rather than learn a pattern that transfers to a new build. All segments from one specimen should remain in the same partition. Preprocessing requires the same discipline. Normalization parameters, PCA loadings, mRMR rankings, and model hyperparameters should be estimated without access to the outer test specimens. Moscovich and Rosset [40] showed that even unsupervised preprocessing can bias cross-validation when it is fitted outside the appropriate resampling loop. Separating trajectory-informed fusion from vibration-only inference, preserving specimen identity, and restricting preprocessing to the training pathway are consequently necessary for a credible cyber-physical evaluation.

## **2.5 Research gaps**

The existing literature provides the essential building blocks for the present investigation. Material extrusion faults have been monitored with vibration and acoustic signals [20–22], raster-angle alterations have been studied using G code and visual surface information [38], and physical side channels have been used for cyber-attack detection [23–25]. These contributions establish that both commanded trajectories and measured process emissions contain useful information. However, they do not fully address how the two forms of evidence should be evaluated when the target class is already encoded in the command file. The first unresolved issue is fine-grained physical state recognition. Most vibration based FDM studies examine nozzle conditions, filament failures, extrusion abnormalities or broad normal vs fault distinctions. The reviewed literature provides limited evidence regarding vibration-based discrimination among seven neighboring raster angle states separated by only 5°. Such states are expected to share substantial motion and structural content. The second gap concerns sensing architecture. Existing raster-angle alteration work relies on layer-wise images [38]. Camera monitoring provides direct surface information, but it requires a clear view of the deposition region and stable imaging conditions. The potential of distributed, low-cost, wireless tri-axial accelerometers for raster-angle verification remains insufficiently examined. The third gap is experimental independence. A large number of windows does not compensate for a small number of independent builds. Evaluation must prevent segments from the same specimen from entering different partitions. Moreover, performance from one test split may depend on which physical specimens were selected. Repeating the evaluation

with different held-out specimens provides a more informative measure of robustness. The fourth gap is the separation of digital and physical evidence. G-code features can accurately describe the intended raster state, while vibration features provide independent evidence of the observed machine response. Combining them may improve classification, but the fused result alone cannot show how much information came from actual execution. A direct comparison between trajectory-informed fusion and vibration-only inference is required. Finally, feature reduction and model development must be audited for leakage. Feature ranking, PCA fitting, normalization, Bayesian optimization, and cross-validation should respect specimen identity. Without these controls, apparently strong performance may result from shared specimen information, test-informed preprocessing, or deterministic command encoding. Table 1 summarizes the key research gaps identified from the literature and shows how they motivate the present study.

Table 1 Summary of research gaps in side-channel monitoring and intrusion detection in AM.

| Research dimension             | Current evidence                                                                                                                        | Research gaps                                                                                               |
|--------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------|
| Material-extrusion monitoring  | Cameras, thermal sensors, acoustic emission, vibration, current, and multi-sensor systems have been investigated [1,2,4,9–12,20–22,46]. | Monitoring performance depends strongly on installation, sensor location, and experimental design.          |
| Raster-angle monitoring        | Raster angle has been modelled as a process parameter [34,37] and alteration has been detected from G-code and layer images [38].       | Limited evidence exists for vibration-based recognition of closely spaced raster angles.                    |
| Direction-dependent response   | Vibration and acoustic signals support FDM condition monitoring [20–22].                                                                | Conventional scalar features may not represent coupled X–Y axis participation.                              |
| Independent evaluation         | Non-independent observations and inappropriate cross-validation procedures can produce optimistic performance estimates. [39–44]        | Windows from one build can leak specimen-specific information across partitions.                            |
| Digital-physical integrity     | G-code, images, acoustic signals, and vibration can reveal process alterations [5–7,23–25,38].                                          | G-code features may identify the intended raster angle without confirming physical execution.               |
| Feature-reduction leakage      | mRMR and PCA are established reduction methods [49,50].                                                                                 | Fitting feature reduction or normalization before resampling can bias evaluation [39,40].                   |
| Reliability and interpretation | Small-sample and model-selection procedures can produce unstable or optimistic performance estimates. [39,42–44]                        | A single accuracy does not reveal specimen sensitivity, neighboring-class confusion, or feature dependence. |

### 3 Methodology

The proposed framework connects the design domain, physical domain, and feature analytics. In the design domain, the CAD geometry is exported as an STL file and sliced to generate G-code containing the commanded toolpath, process settings, and raster orientation. The highlighted G-code stage identifies a potential point at which the commanded raster angle could be altered. In the physical domain, printing-induced vibrations are acquired using four independent wireless sensing nodes, each comprising an ADXL345 tri-axial accelerometer and an ESP32 microcontroller. One node monitors the nozzle assembly, while three nodes monitor the print bed. The measurements are transmitted over Wi-Fi to a Flask acquisition server and stored as timestamped batches for subsequent analysis. The feature-analytics stage integrates information from the commanded trajectory and measured vibration response. The vibration segments are resampled to a common length, after which time-domain, directional cross-axis, wavelet-packet energy, and wavelet-packet energy-ratio features are extracted. These descriptors are fused with G-code trajectory features and standardized using statistics estimated from the combined development data. Minimum-

redundancy maximum-relevance (mRMR) selection then identifies an informative feature subset for classification using a Bayesian-optimized Gaussian error-correcting output-code support vector machine (ECOC-SVM). Fig. 4 presents the proposed framework for trajectory-informed raster-angle state identification in material-extrusion printing.

### 3.1 G-code trajectory formulation

Let  $(X_i, Y_i)$  denote the planar position associated with the  $i$ -th G-code motion command. When either coordinate was omitted from a command, its most recently specified value was retained. The planar displacement, travel distance, and movement direction between consecutive commands were calculated as shown in Eq. (1).

$$\begin{aligned}\Delta X_i &= X_i - X_{i-1}; \quad \Delta Y_i = Y_i - Y_{i-1}; \quad d_i = \sqrt{(\Delta X_i)^2 + (\Delta Y_i)^2}; \\ \theta_i &= \text{atan2d}(\Delta Y_i, \Delta X_i), \quad -180^\circ \leq \theta_i \leq 180^\circ.\end{aligned}\tag{1}$$

Zero-distance movements were removed because they do not define a planar direction. Let  $M$  denote the number of remaining movements. Because angular values were wrapped around at  $-180^\circ$  and  $180^\circ$ , circular statistics were used to describe the movement directions, as shown in Eq. (2).

$$\begin{aligned}L_p &= \sum_{i=1}^M d_i, \quad \bar{C} = \frac{1}{M} \sum_{i=1}^M \text{cosd}(\theta_i), \quad \bar{S} = \frac{1}{M} \sum_{i=1}^M \text{sind}(\theta_i). \\ \theta_{\text{mean}} &= \text{atan2d}(\bar{S}, \bar{C}), \quad R = \sqrt{\bar{C}^2 + \bar{S}^2}. \\ \sigma_\theta &= \frac{180}{\pi} \sqrt{-2 \ln(\min(1, \max(R, \varepsilon)))}\end{aligned}\tag{2}$$

Where,  $M$  is the number of valid planar movements,  $L_p$  is the total planar toolpath length,  $\theta_{\text{mean}}$  is the circular mean direction,  $R$  is the circular resultant length,  $\sigma_\theta$  is the circular standard deviation, and  $\varepsilon$  is a small positive constant used for numerical stability. Distance-weighted X- and Y-axis dominance and their relative balance were calculated as (3).

$$D_x = \frac{\sum_{i=1}^M |\text{cosd}(\theta_i)| d_i}{L_p + \varepsilon}, \quad D_y = \frac{\sum_{i=1}^M |\text{sind}(\theta_i)| d_i}{L_p + \varepsilon}\tag{3}$$

Their relative balance was represented using the following formation, shown in Eq. (4).

$$D_{xy} = \frac{D_x}{D_y + \varepsilon}\tag{4}$$

Consecutive direction changes were converted to absolute angular differences and wrapped to the interval  $0^\circ$ – $180^\circ$ . Their mean, standard deviation, and the fraction of direction changes exceeding  $45^\circ$  were used to characterize toolpath turning behavior. The overall movement-direction distribution was represented using an 18-bin normalized histogram spanning  $-180^\circ$  to  $180^\circ$ . These directional quantities were combined with the total toolpath length, coordinate ranges, feed-rate statistics, move-distance statistics, circular descriptors, and dominance variables, producing 34 G-code trajectory features for each observation.

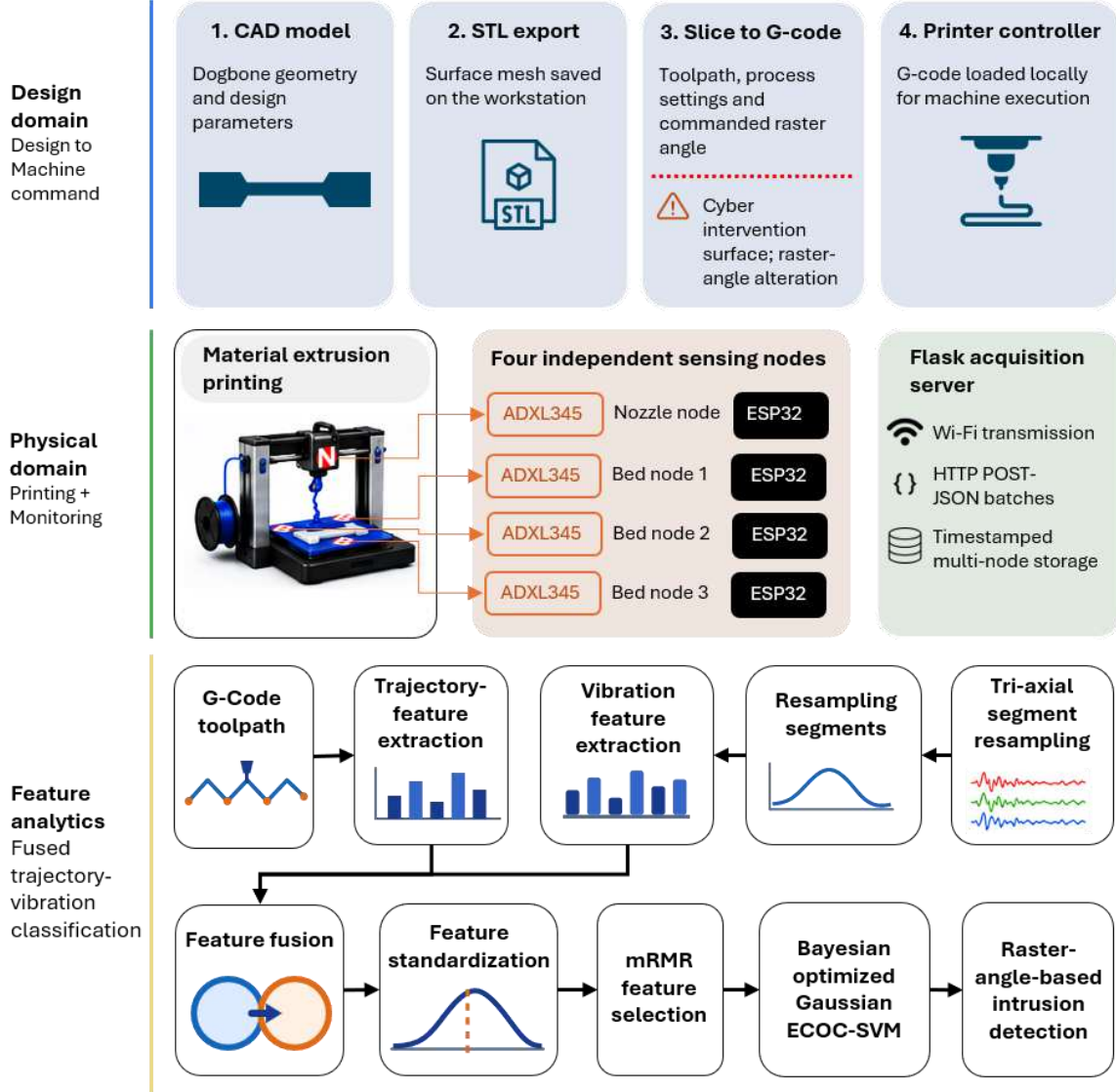


Fig. 4 Overview of the proposed trajectory-informed framework for raster-angle state identification, showing CAD-to-G-code preparation, wireless vibration acquisition, and feature analytics comprising trajectory–vibration fusion, standardization, mRMR feature selection, and Bayesian-optimized Gaussian ECOC-SVM classification.

### 3.2 Vibration-signal preprocessing

Each raw vibration observation consisted of tri-axial acceleration samples acquired at a nominal application-level sampling rate of 250 Hz, shown in Eq. (5)

$$[x(n), y(n), z(n)]^T, \quad n = 1, \dots, N. \quad (5)$$

For the trajectory-informed pipeline, each tri-axial observation was resampled to 8192 points and subsequently normalized channel-wise using a within-observation z-score transformation before deterministic feature extraction. A second feature-level standardization was applied later using statistics calculated from the development set, as described in Section 3.6.

### 3.3 Time-domain vibration descriptors

For a resampled vibration channel,  $a(n)$ , where  $a \in \{x, y, z\}$ , the principal magnitude-based descriptors were calculated as shown in Eq. (6),

$$\begin{aligned} \text{RMS}_a &= \sqrt{\frac{1}{N} \sum_{n=1}^N a^2(n)}; \quad \sigma_a = \sqrt{\frac{1}{N-1} \sum_{n=1}^N [a(n) - \bar{a}]^2}; \quad \text{MAV}_a = \frac{1}{N} \sum_{n=1}^N |a(n)| \\ P_a &= \max_n |a(n)|; \quad \text{PP}_a = \max_n a(n) - \min_n a(n); \quad \text{CF}_a = \frac{P_a}{\text{RMS}_a + \varepsilon} \end{aligned} \quad (6)$$

Here,  $\text{RMS}_a$ ,  $\sigma_a$ ,  $\text{MAV}_a$ ,  $P_a$ ,  $\text{PP}_a$ ,  $\text{CF}_a$ , and  $E_a$  denote the root-mean-square value, standard deviation, mean absolute value, absolute peak, peak-to-peak range, crest factor, and mean-square signal value, respectively. Skewness and kurtosis were additionally calculated to characterize signal asymmetry and distributional shape. Thus, nine time-domain descriptors were obtained from each vibration channel. Application of these descriptors to the three acceleration channels produced 27 time-domain features. Although RMS and mean-square signal value are mathematically related, both were retained to preserve correspondence with the implemented feature-extraction procedure.

### 3.4 Directional cross-axis features

Directional features were used to represent the relative participation and coupled response of the vibration axes. For the X–Y channel pair, the principal relationships were calculated as shown in Eq. (7),

$$\begin{aligned} \rho_{xy} &= \frac{\sum_{n=1}^N [x(n) - \bar{x}] [y(n) - \bar{y}]}{(N-1)\sigma_x\sigma_y} \\ R_{xy}^{\text{RMS}} &= \frac{\text{RMS}_x}{\text{RMS}_y + \varepsilon}; \quad R_{xy}^E = \frac{E_x}{E_y + \varepsilon} \\ \alpha_{xy} &= \text{atan2d}(\text{RMS}_y, \text{RMS}_x) \\ \phi(n) &= \text{atan2d}(y(n), x(n)) \end{aligned} \quad (7)$$

Here,  $\rho_{xy}$  denotes the X–Y correlation coefficient,  $R_{xy}^{\text{RMS}}$  and  $R_{xy}^E$  denote the X/Y RMS and mean-square energy ratios,  $\alpha_{xy}$  denotes the RMS-based X–Y orientation angle, and  $\phi(n)$  denotes the instantaneous planar vibration direction. Pairwise correlation coefficients were calculated for X–Y, X–Z, and Y–Z. Reciprocal X/Y and Y/X RMS and energy ratios were included, together with RMS-based orientation angles for the X–Y, X–Z, and Y–Z axis pairs. The circular mean, circular standard deviation, circular resultant length, and an 18-bin normalized histogram were calculated from  $\phi(n)$ . Together, these quantities produced 31 directional variables for the trajectory-informed pipeline.

### 3.5 Wavelet-packet energy representation

Wavelet-packet decomposition recursively decomposes both approximation and detail coefficients. At decomposition level  $L$ , the number of terminal nodes is  $N_{\text{nodes}} = 2^L$ . The implemented level was  $L = 4$ ,  $N_{\text{nodes}} = 16$ . Let  $w_{c,j}(k)$  denote the wavelet-packet coefficient at sample  $k$ , terminal node  $j$ , and vibration channel  $c$ . The raw and normalized energies of each terminal node were calculated as

$$E_{c,j} = \sum_k |w_{c,j}(k)|^2; \quad \hat{E}_{c,j} = \frac{E_{c,j}}{\sum_{m=1}^{2^L} E_{c,m} + \varepsilon} \quad (8)$$

Sixteen normalized terminal-node energies were extracted from each vibration channel, resulting in 48 WPT energy features across the three axes. To characterize the relative distribution of sub band energy among the vibration axes, three cross-channel energy ratios were calculated for every terminal node as shown in Eq. (9),

$$R_{xy,j} = \frac{\hat{E}_{x,j}}{\hat{E}_{y,j} + \varepsilon} ; R_{yz,j} = \frac{\hat{E}_{y,j}}{\hat{E}_{z,j} + \varepsilon} ; R_{xz,j} = \frac{\hat{E}_{x,j}}{\hat{E}_{z,j} + \varepsilon} \quad (9)$$

The three ratios calculated over the 16 terminal nodes produced 48 additional WPT-energy-ratio features. These ratios describe the relative distribution of frequency-dependent vibration energy among the three sensor axes.

### 3.6 Feature fusion, standardization, and mRMR selection

For observation  $i$ , let  $t_i$ ,  $d_i$ ,  $e_i$ ,  $q_i$ , and  $g_i$  denote the time-domain, directional cross-axis, WPT-energy, WPT-energy-ratio, and G-code trajectory feature vectors, respectively. The vibration representation and the complete fused representation were defined as  $v_i = [t_i^T \ d_i^T \ e_i^T \ q_i^T]^T$ , and  $x_i = [v_i^T \ g_i^T]^T \in \mathbb{R}^p$ , where  $p$  denotes the total number of candidate features in the fused representation. After deterministic feature extraction and fusion, the nominal training and validation subsets were combined to form the development set. Each feature was standardized using statistics calculated from the development observations. For feature  $j$  of observation  $i$ , the standardized value was calculated as  $\frac{x_{i,j} - \mu_{j,\text{dev}}}{\sigma_{j,\text{dev}} + \varepsilon}$ , where  $\mu_{j,\text{dev}}$  and  $\sigma_{j,\text{dev}}$  are the mean and standard deviation of feature  $j$  calculated from the development observations. The same parameters were applied unchanged to the held-out test observations. Any nonfinite values caused by a zero-variance feature were replaced with zero. The fused representation may contain redundant variables because multiple feature families can describe related properties of the same signal. Minimum-redundancy maximum-relevance feature selection was therefore used to identify features that were informative about the raster-angle class while minimizing repeated information among the selected variables [49]. Let  $\Omega$  denote the complete candidate-feature set,  $\mathcal{S}_{t-1}$  the set of features selected before iteration  $t$ , and  $r$  the raster-angle class label. The feature selected at iteration  $t$  was defined as shown in Eq. (10)

$$f_t^* = \arg \max_{f \in \Omega \setminus \mathcal{S}_{t-1}} \left[ I(f; r) - \frac{1}{|\mathcal{S}_{t-1}|} \sum_{h \in \mathcal{S}_{t-1}} I(f; h) \right] \quad (10)$$

Where,  $I(\cdot; \cdot)$  denotes mutual information. For the first iteration, when the selected set is empty, the feature having the highest mutual information with the class label is selected. After  $k$  iterations, the selected feature set is shown in Eq. (11)

$$\mathcal{S}_k = \{f_1^*, f_2^*, \dots, f_k^*\} \quad (11)$$

and the corresponding reduced feature vector for observation  $i$  is denoted by

$$u_i = [\tilde{\mathbf{x}}_{i,\mathcal{S}_k}] \quad (12)$$

The mRMR ranking was fitted once to the standardized development matrix. The retained feature count  $k$  was treated as a model-selection parameter, and candidate feature counts were evaluated using five-fold cross-validation within the development data. The feature count producing the lowest cross-validation loss was retained. The mRMR ranking

was not recomputed separately within each inner cross-validation fold, and the held-out test specimens were excluded from both feature ranking and feature-count selection.

### 3.7 Bayesian-optimized Gaussian ECOC-SVM

The mRMR-selected fused feature representation was classified using Gaussian-kernel SVM learners [51]. For two selected feature vectors  $\mathbf{u}_i$  and  $\mathbf{u}_j$ , the Gaussian kernel was defined in Eq. (13), where  $\ell > 0$  is the Gaussian kernel-scale parameter.

$$K(\mathbf{u}_i, \mathbf{u}_j) = \exp \left[ -\frac{\|\mathbf{u}_i - \mathbf{u}_j\|_2^2}{2\ell^2} \right] \quad (13)$$

Multiclass classification was implemented using a one-versus-one ECOC design. Each binary SVM learner distinguished between one pair of raster-angle classes, and the outputs of all pairwise learners were combined to obtain the final predicted class. Bayesian optimization was used to determine the SVM box constraint and Gaussian kernel scale [52,53]. The optimization problem was formulated in Eq. (14)

$$(C_{SVM}^*, \ell^*) = \arg \min_{C_{SVM} > 0, \ell > 0} \mathcal{L}_{CV}(C_{svm}, \ell) \quad (14)$$

Where,  $C_{SVM}$  is the box-constraint parameter and  $\mathcal{L}_{CV}$  is the cross-validation classification loss calculated using only the development data. The expected improvement-plus acquisition strategy was used with a maximum of 30 objective evaluations. Bayesian optimization and classifier development were performed using the development representation obtained after standardization and mRMR selection. The held-out test specimens remained completely isolated from standardization, mRMR ranking, feature-count selection, hyperparameter optimization, and classifier training. After the feature count and SVM hyperparameters were selected, the resulting development-set model was used to predict the held-out test observations once. The inner cross-validation folds were formed at the observation level within the development data. Consequently, observations originating from the same physical specimen could occur in different inner folds. In addition, development-set standardization and mRMR ranking were performed before feature-count cross-validation rather than being recomputed within each inner training fold. These operations did not expose the outer test specimens to model development, but the inner procedure was not fully nested and may influence model-selection estimates.

### 3.8 Evaluation metrics

For every run, the initial specimen-level allocation produced 49 training specimens, 14 validation specimens, and seven test specimens. Because the nominal training and validation subsets were subsequently combined for model development, the effective development set contained 63 specimens, while seven specimens remained held out for final testing. With four observations per specimen, this corresponded to 252 development observations and 28 held-out test observations. Multiclass test accuracy was calculated as Eq. (15). For class  $c$ , precision, recall and F-1 scores are calculated in Equations (16), (17) and (18), respectively. Macro-averaged precision, recall, and F1-score were obtained by averaging the corresponding values across the seven raster-angle classes.

$$\text{Accuracy} = \frac{\sum_{i=1}^{N_{\text{test}}} \mathbb{1}(\hat{Y}_i = Y_i)}{N_{\text{test}}} \times 100\% \quad (15)$$

$$\text{Precision}_c = \frac{TP_c}{TP_c + FP_c} \quad (16)$$

$$\text{Recall}_c = \frac{TP_c}{TP_c + FN_c} \quad (17)$$

$$F1_c = \frac{2 \text{ Precision}_c \text{ Recall}_c}{\text{Precision}_c + \text{Recall}_c} \quad (18)$$

#### 4 Experimental setup

A Prusa MK4S material-extrusion 3D printer was used to fabricate 70 dogbone specimens representing seven raster-angle classes, ranging from 45° to 75° in increments of 5°. Ten independent specimens were produced for each class. The specimen geometry and nominal printing settings were held constant while the raster angle was varied. Fig. 5 shows the printing platform, wireless sensing arrangement, and computer-based data-acquisition system. The G-code

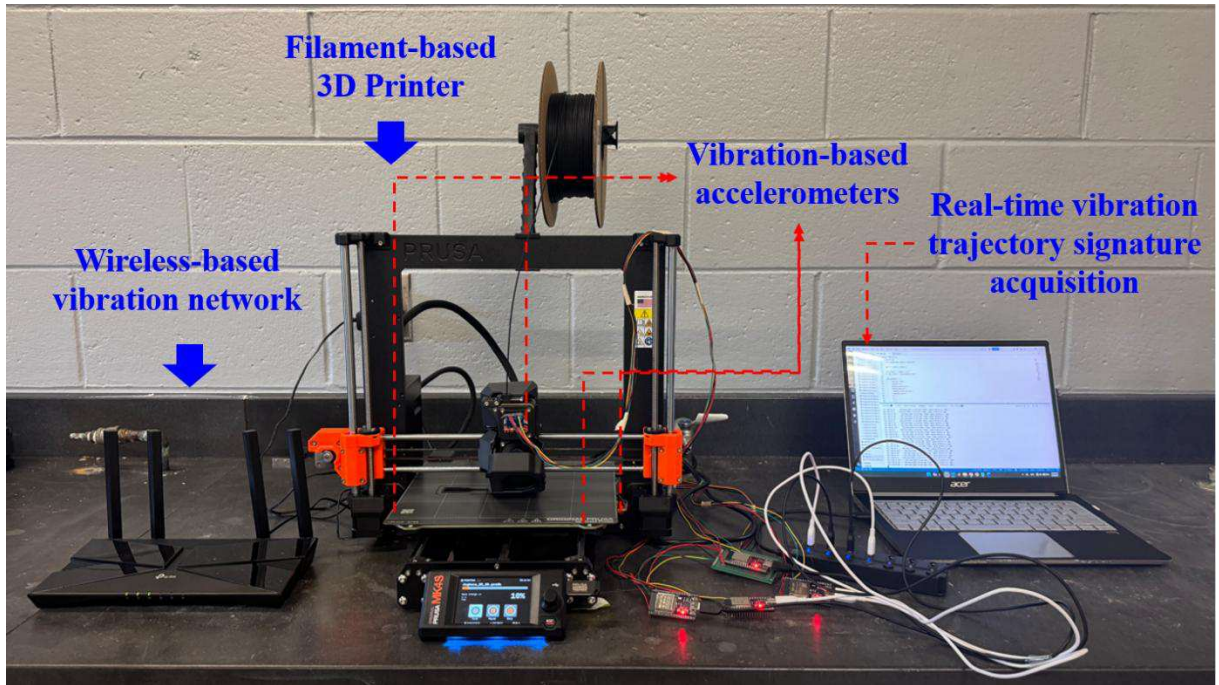


Fig. 5 Experimental setup for wireless vibration monitoring during material-extrusion printing, showing the Prusa MK4S printer, ADXL345 tri-axial accelerometers connected to ESP32 sensing nodes, Wi-Fi router, and computer-based data-acquisition system.

files were generated using PrusaSlicer 2.9.4. The archived metadata specified PLA filament, a 0.4 mm nozzle, a nominal layer height of 0.30 mm, and a first-layer height of 0.35 mm. The slicing configuration used 100% rectilinear infill, three perimeters, three top solid layers, and three bottom solid layers. The nozzle temperature was set to 215 °C, while the bed temperature was set to 65 °C for the first layer and 60 °C for subsequent layers. The profiles specified

nominal perimeter, infill, solid-infill, small-perimeter, and travel speeds of 30 mm/s, with a maximum print-speed setting of 80 mm/s.

#### 4.1 Wireless data acquisition

Tri-axial vibration measurements were acquired using four ADXL345 accelerometers, each connected to an independent ESP32 microcontroller; one node was positioned near the nozzle or printhead assembly and three were mounted on the print-bed structure. The ADXL345 sensors were configured to a  $\pm 4$  g range and an internal data rate of 800 Hz, while the ESP32 requested one tri-axial sample every 0.004 s, corresponding to a nominal acquisition rate of 250 Hz. Acceleration was recorded in  $\text{m/s}^2$ . Each node buffered up to 1000 samples over a nominal 4 s acquisition interval and stored relative sample time together with the X-, Y-, and Z-axis measurements. After each interval, the buffered data were transmitted over Wi-Fi to a Flask-based server through HTTP POST using a plain-text CSV-formatted payload containing the sensor identifier, batch timing, sampling interval, sample count, and tri-axial measurements. The four sensing nodes operated independently without a shared hardware clock or explicit cross-node synchronization; malformed sample rows were skipped by the server, and failed batches were not retransmitted.

#### 4.2 G-code files and commanded trajectory structure

Seven class-specific G-code files were analyzed, one for each raster-angle setting. Each file contained 11 layer-change markers. The G0 and G1 motion commands were processed using the trajectory formulation described in Section 3.1 to obtain 34 G-code descriptors per file. The analyzed toolpaths included perimeter, infill, solid-infill, travel, skirt or brim, and layer-transition movements, allowing the descriptors to characterize the complete commanded planar motion sequence. Fig. 6 shows the dogbone specimen and enlarged surface regions corresponding to the seven raster-angle states.

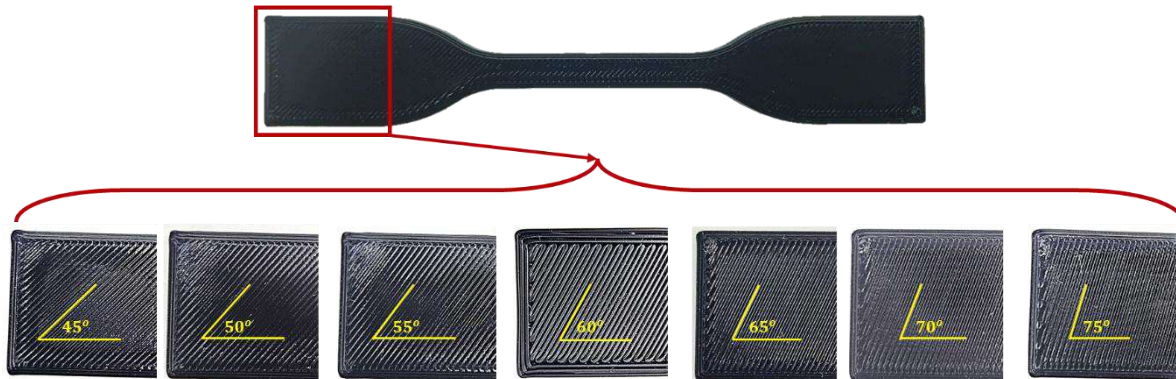


Fig. 6 Material-extrusion dogbone specimen and enlarged surface regions representing the seven commanded raster-angle states: 45°, 50°, 55°, 60°, 65°, 70°, and 75°.

##### 4.2.1 G-code trajectory characteristics

The commanded trajectories showed clear raster-angle-dependent differences across the seven classes. Fig. 7 shows the normalized motion-direction distributions obtained from the complete G-code trajectories. Although the seven raster-angle classes share common motion components associated with the fixed specimen geometry, perimeter paths, travel movements, and layer transitions, clear class-dependent shifts are observed in several angular regions. These

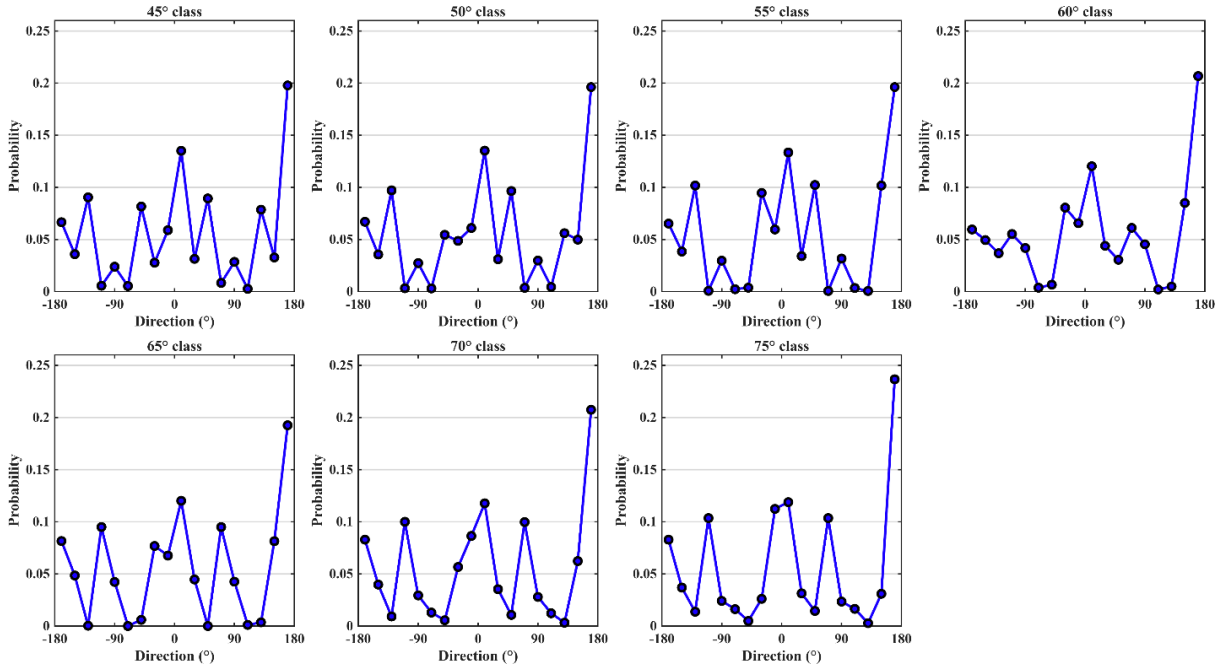


Fig. 7 Normalized G-code motion-direction distributions for the seven class-specific command files. Each graph contains 18 bins spanning  $-180^{\circ}$  to  $180^{\circ}$  in  $20^{\circ}$  increments.

differences indicate that the commanded raster orientation produces a measurable change in the overall directional composition of the toolpath, even when adjacent raster-angle settings remain geometrically similar. The trajectory-level descriptors in Fig. 8 further quantify these differences. Total path length and the X/Y dominance ratio vary across the raster-angle settings, while the circular resultant length and sharp-turn fraction characterize changes in directional concentration and trajectory complexity. The observed trends are not strictly monotonic because the descriptors are calculated from the complete motion sequence rather than from in-fill trajectories alone. Consequently, the resulting values reflect the combined influence of raster orientation, fixed specimen geometry, perimeter motion, travel, and transition commands. Fig. 9 presents the standardized values of the 34 extracted G-code trajectory descriptors. Each raster-angle class exhibits a distinct command-feature pattern, demonstrating that the G-code representation contains strong class-specific information about the intended manufacturing state. Because all specimens within a given class were generated from the same class-specific command structure, these descriptors provide a deterministic representation of the commanded raster angle. This observation is important for interpreting the subsequent classification results, since G-code-derived separability should be distinguished from state information inferred independently from the measured vibration response

### Selected G-code Trajectory Descriptors

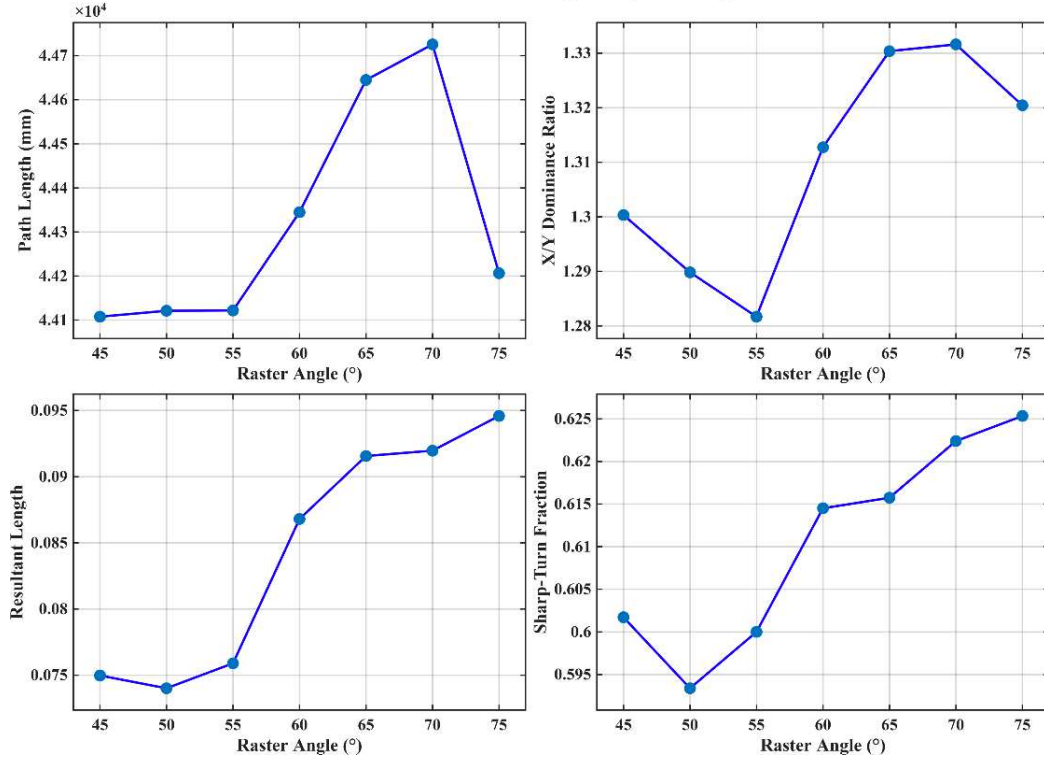


Fig. 8 Class-wise variation of selected G-code trajectory descriptors: accumulated path length, X/Y dominance ratio, circular resultant length, and fraction of sharp direction changes.

### 4.3 Dataset hierarchy and specimen-aware splitting

Each of the 70 physical specimens contributed four tri-axial sensor observations, resulting in 280 observations. For each run, specimens were randomized independently within each raster-angle class. Seven specimens per class were initially assigned to training, two to validation, and one to testing, producing 49 training, 14 validation, and seven test specimens. The corresponding observation counts were 196, 56, and 28. In the archived implementation, the training

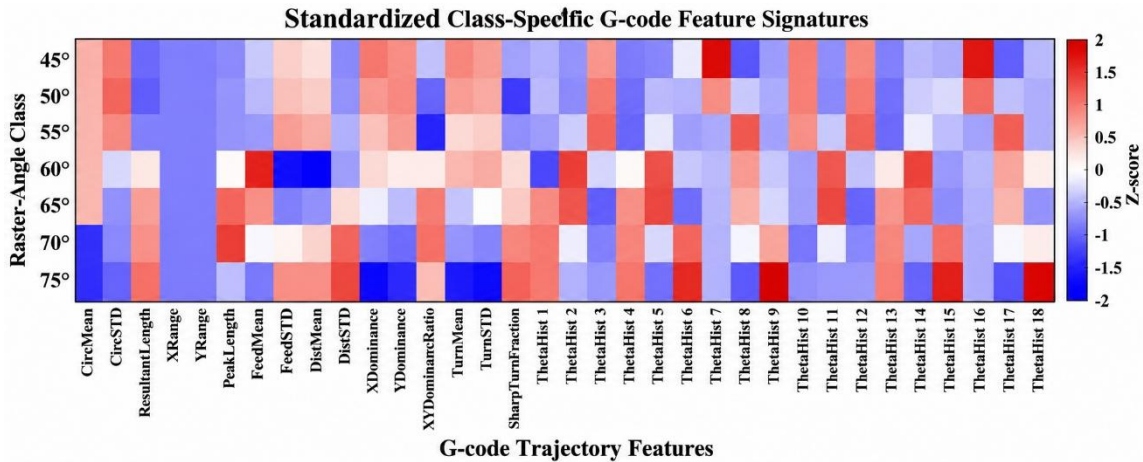


Fig. 9 Standardized 34-feature G-code signatures for the seven raster-angle classes. Each row is unique, demonstrating that the archived command representation directly identifies the intended class.

and validation subsets were combined before preprocessing and model selection. The effective development set therefore contained 63 specimens and 252 segments, while seven specimens and 28 segments remained isolated for final testing. The nominal validation subset did not serve as a separate held-out validation set; its observations were incorporated into the development set, which is demonstrated in Table 2. The outer specimen-level partition prevented direct overlap between development and test specimens. Inner model selection used five-fold observation-level cross-validation within the development set. Because segments from the same development specimen could occur in different inner folds, and because some preprocessing operations were fitted before inner cross-validation, the procedure was not fully nested.

Table 2 Dataset hierarchy and outer specimen-level partition used in each run.

| Dataset element                           | Count               |
|-------------------------------------------|---------------------|
| Raster-angle classes                      | 7                   |
| Specimens per class                       | 10                  |
| Physical specimens                        | $7 \times 10 = 70$  |
| Sensor observations per specimen          | 4                   |
| Total sensor observations                 | $70 \times 4 = 280$ |
| Training specimens per run                | 49                  |
| Validation specimens per run              | 14                  |
| Combined development specimens per run    | $49 + 14 = 63$      |
| Test specimens per run                    | 7                   |
| Training observations per run             | 196                 |
| Validation observations per run           | 56                  |
| Combined development observations per run | $196 + 56 = 252$    |
| Test observations per run                 | 28                  |

## 5 Results and discussion

The results are presented through direct comparison of the proposed trajectory-informed WPT–mRMR–SVM pipeline and the vibration-only directional WPT–PCA–SVM benchmark. Both pipelines were evaluated using the same five repeated specimen-level splits and the same held-out test specimens within each split. The comparison considers feature-space organization, class-specific prediction behavior, and run-wise test performance. However, the results represent a comparison between two complete analytical pipelines rather than an isolated comparison of mRMR and PCA. The proposed pipeline incorporates both G-code trajectory descriptors and vibration-derived features, whereas the benchmark relies exclusively on vibration-derived information.

### 5.1 Feature-space visualization and class separability

The proposed pipeline retained ten predictors from the fused trajectory–vibration feature space using mRMR, whereas the benchmark represented the vibration-only feature space using nine principal components. Fig. 10 presents representative t-SNE visualizations for Runs 1 and 4. In Fig. 10 (a) and (c), the trajectory-informed representations form several compact and relatively well-separated groups. The inclusion of G-code descriptors provides direct information about commanded toolpath direction and therefore contributes to separation among raster-angle states. The benchmark methods outcome represented in Fig. 10 (b) and (d) also show distinguishable class structure,

demonstrating that the measured vibration response contains raster-angle-dependent information. However, greater overlap is observed among several intermediate and higher raster-angle states. Run 4 shows clearer organization than Run 1, consistent with the corresponding increase in benchmark accuracy from 89.29% to 96.43%. The t-SNE plots are intended only for qualitative visualization. Because the two pipelines use different high-dimensional feature representations, the absolute positions, orientations, and distances of their t-SNE projections should not be compared directly. Furthermore, two-dimensional overlap does not necessarily indicate that the Gaussian ECOC-SVM cannot separate the corresponding classes. Classification performance is therefore assessed primarily using the held-out confusion matrices and test metrics.

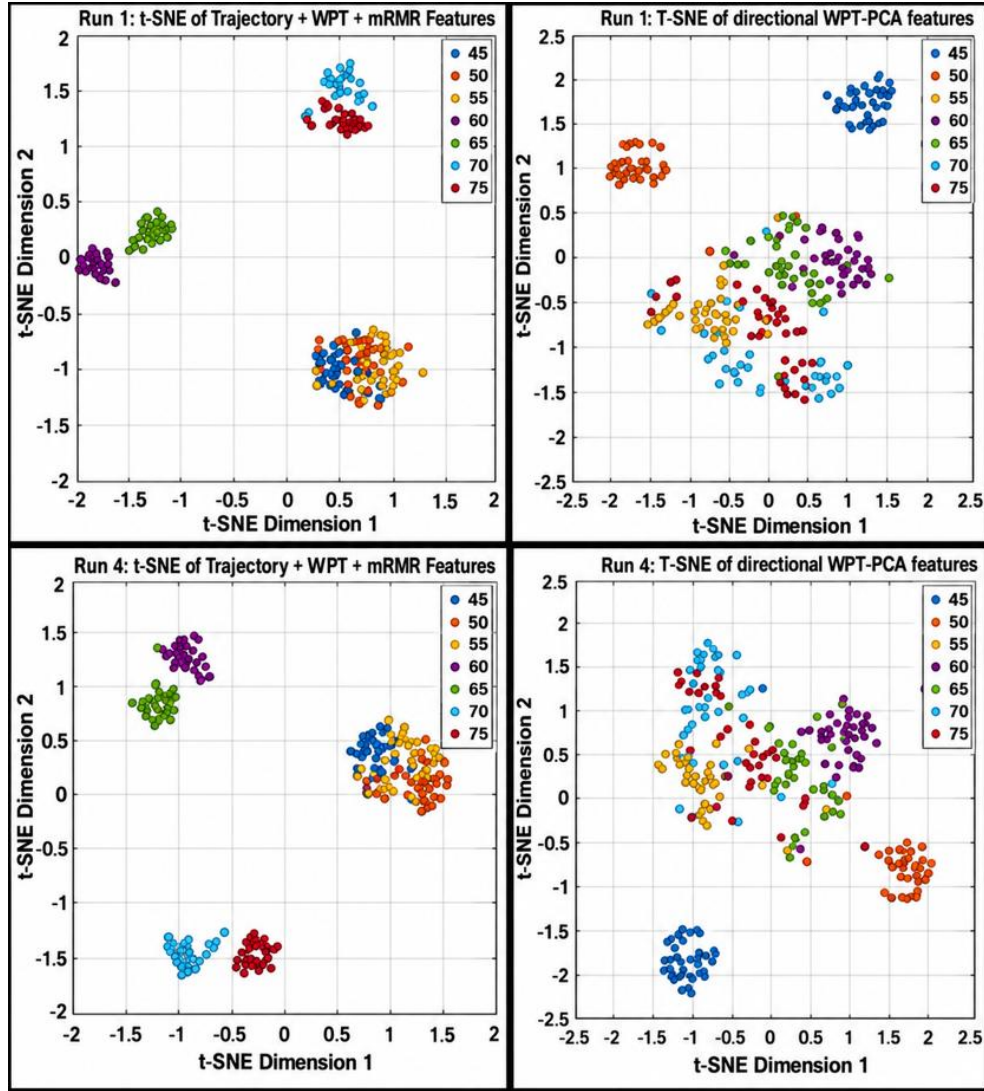


Fig. 10 Comparative t-SNE visualization of the proposed (a, c) and benchmark (b, d) methods for Runs 1 and 4, using 10 mRMR-selected features and nine PCA components across all 280 observations.

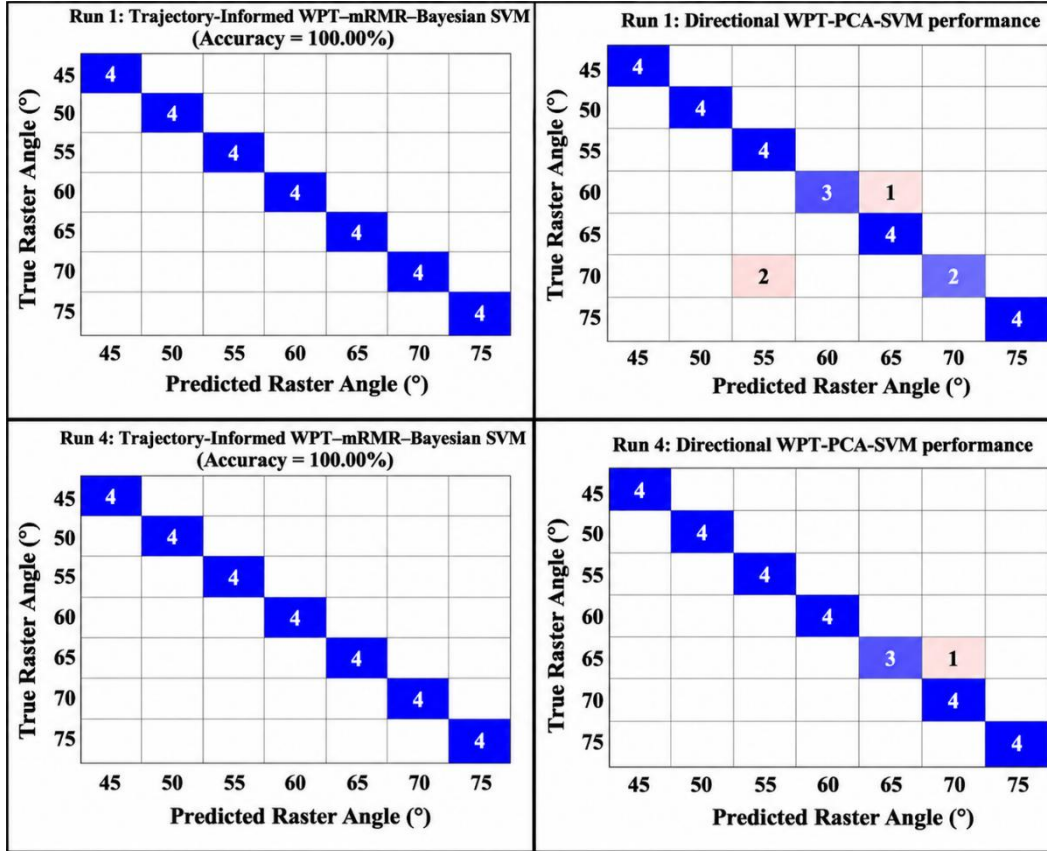


Fig. 11 Paired held-out confusion matrices for the proposed (a, c) and benchmark (b, d) methods for Runs 1 and 4, achieving 100% accuracy for the proposed method versus 89.29% and 96.43% for the benchmark.

## 5.2 Classification performance and error analysis

Fig. 11 compares the held-out confusion matrices for Runs 1 and 4. Each test split contained 28 observations, consisting of four sensor observations from one held-out specimen for each of the seven raster-angle classes. The proposed pipeline correctly classified all observations in both runs and achieved the same result across the remaining three splits. It therefore produced 100% test accuracy, precision, recall, and F1-score for all classes across the five evaluations. The benchmark showed greater variation. In Run 1, 25 of 28 observations were correctly classified, producing an accuracy of 89.29%. One 60° observation was classified as 65°, and two 70° observations were classified as 55°. In Run 4, 27 of 28 observations were correctly classified, giving an accuracy of 96.43%; the only error involved one 65° observation classified as 70°. Across the five runs, the benchmark produced mean class-level F1-scores of 100.00%, 100.00%, 86.48%, 90.48%, 85.47%, 59.11%, and 97.78% for the 45°, 50°, 55°, 60°, 65°, 70°, and 75° states, respectively. The lower F1-score for the 70° state indicates greater overlap between its vibration response and those of other states under the present experimental conditions. Fig. 12 summarizes test accuracy across all five specimen-level splits. The proposed pipeline achieved 100% accuracy in every run. The vibration-only benchmark achieved 89.29%, 78.57%, 89.29%, 96.43%, and 96.43% accuracy in Runs 1–5, respectively, corresponding to a mean of 90.00% and a sample standard deviation of 7.32 percentage points. The 10-percentage-point difference in mean

accuracy reflects both the different feature representations and, importantly, the availability of deterministic G-code trajectory information in the proposed pipeline. Its 100% accuracy should therefore be interpreted as reliable trajectory-informed identification of the commanded state, not as evidence that mRMR is inherently superior to PCA. In contrast, the benchmark result demonstrates that raster-angle state can be estimated with relatively high accuracy from vibration measurements alone. A direct comparison of mRMR and PCA would require both methods to operate on the same initial feature matrix using identical preprocessing and classifier-evaluation conditions. Table 3 presents the Bayesian-optimized Gaussian ECOC-SVM hyperparameters for the five evaluation runs. The selected box constraint ( $C$ ) and kernel scale ( $\ell$ ) varied considerably across runs, and each reported run attained a minimum observed inner cross-validation loss of zero. Because the hyperparameter combinations were obtained from different development partitions, these results should not be interpreted as demonstrating equivalent parameter settings on a common dataset. The selected parameters were subsequently used to train the corresponding run-specific classifiers before evaluation of the isolated test specimens.

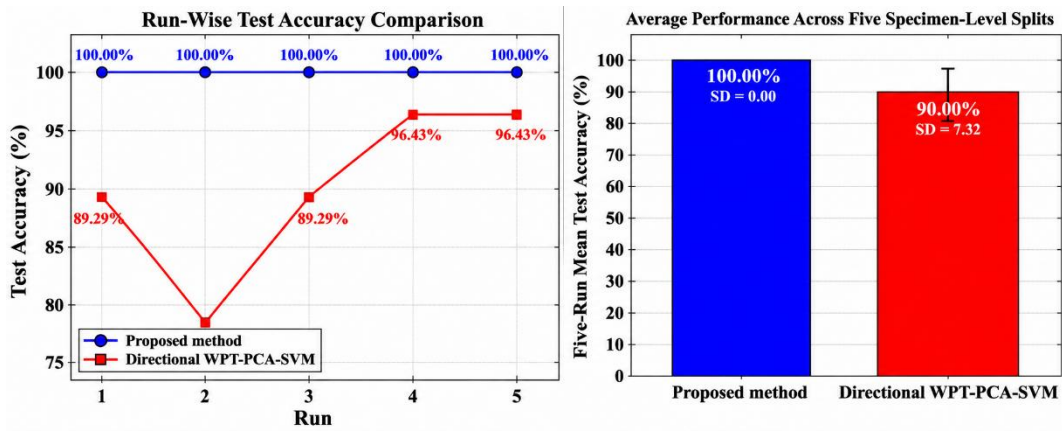


Fig. 12 Performance comparison of the proposed and benchmark methods: (a) run-wise test accuracy and (b) five-run mean  $\pm$  SD, achieving  $100.00\% \pm 0.00\%$  and  $90.00\% \pm 7.32\%$ , respectively.

Table 3 Bayesian-optimized Gaussian ECOC-SVM hyperparameters across the five evaluation runs

| Optimized hyperparameters | Run 1  | Run 2  | Run 3  | Run 4     | Run 5  |
|---------------------------|--------|--------|--------|-----------|--------|
| Box constraint ( $C$ )    | 1.7054 | 954.44 | 4.4432 | 0.0059506 | 104.88 |
| Kernel scale ( $\ell$ )   | 17.621 | 43.572 | 24.125 | 5.1023    | 50.766 |

### 5.3 Cyber-physical and manufacturing-system significance

The separation between commanded trajectory information and vibration-based physical evidence provides a basis for future cyber-physical integrity monitoring. Such verification would require the intended manufacturing state to be established from a trusted reference, such as an authenticated job specification or verified G-code, independently of any potentially altered execution command. The trusted intended state could then be compared with an independently estimated vibration-based physical state. Persistent disagreement could indicate execution deviation, process disturbance, sensing abnormality, command inconsistency, or possible manipulation. Conversely, agreement between

the vibration response and a potentially altered command file would indicate consistency between those two sources but would not, by itself, establish that the originally intended manufacturing configuration had been preserved. The present experiments did not introduce command–process mismatches or cyberattacks and therefore do not demonstrate anomaly- or attack-detection performance. Rather, they establish the digital and physical information pathways needed for such future verification. The wireless ESP32-based sensing architecture also provides a practical retrofit approach because the accelerometer nodes operate independently of the printer controller and transmit measurements to an external processing system. This design can support future integration with manufacturing monitoring, digital-twin, traceability, and cybersecurity frameworks without modifying the printer's internal motion-control system. The estimated raster-angle state should nevertheless be considered a process-state indicator rather than a direct measure of final product quality. It is therefore complementary to dimensional inspection, surface monitoring, mechanical testing, and other quality-assurance methods.

#### **5.4 Reliability, uncertainty and evaluation limitations**

The dataset contained 70 independently printed specimens, with ten specimens for each raster-angle class. The outer partitioning was performed at the specimen level so that all four observations associated with a physical specimen remained together. After the initial training and validation allocation, these subsets were combined into the development set, while seven specimens, one from each class, remained isolated for final testing. Consequently, each test split contained 28 observation-level predictions but only seven independent physical specimens. The five repeated specimen-level evaluations therefore provide a more meaningful indication of sensitivity to specimen selection than the number of individual observations alone. A further limitation concerns the inner model-selection procedure. Although the outer test specimens remained completely isolated, five-fold cross-validation within the development set was performed at the segment level, allowing observations from the same physical specimen to occur in different inner folds. In addition, standardization and mRMR ranking for the trajectory-informed pipeline, and standardization and PCA for the benchmark, were fitted using the complete development set before the corresponding inner cross-validation evaluations rather than being recomputed within each inner training fold. These choices may introduce optimistic bias into the model-selection estimates, although their influence on the reported outer-test performance cannot be quantified without rerunning the analysis. A stricter evaluation should therefore use specimen-grouped inner folds with all data-dependent preprocessing, feature-selection or dimensionality-reduction operations, and hyperparameter optimization nested within each inner training fold. Generalization is also limited by experimental scope. The study considered one printer, one specimen geometry, one nominal material and process configuration, and one wireless sensor arrangement. The four ESP32 sensing nodes operated independently without explicit cross-node clock synchronization, and vibration characteristics may also vary with machine structure, process settings, material properties, sensor position, and mounting conditions. Additional experiments across multiple printers, sensor placements, materials, geometries, and operating conditions are therefore required before broader deployment. Finally, the current class labels represent raster-angle states rather than defects, attacks, or mechanical degradation. The reported results therefore quantify commanded-state identification and vibration-based physical-state estimation only. Controlled anomaly and command–process mismatch experiments will be required to establish defect- or cyberattack-detection capability.

## 6 Conclusion and future outlook

This study developed a wireless vibration and G-code trajectory-informed cyber-physical ML framework for raster angle state identification in material extrusion additive manufacturing. Four ADXL345 tri-axial accelerometers, each connected to an individual ESP32 module, were used to acquire vibration signals and transmit them wirelessly to an external server without modifying the printer controller. Seven closely spaced raster-angle states, ranging from  $45^\circ$  to  $75^\circ$  in  $5^\circ$  increments, were investigated using 70 independently printed dogbone specimens and 280 sensor-specific tri-axial vibration observations. Two complementary analytical pathways were evaluated: a proposed trajectory-informed WPT–mRMR–SVM model combining G-code trajectory descriptors with vibration features, and a vibration-only WPT–PCA–SVM benchmark. Specimen identity was preserved during the outer training, validation, and testing partitions to prevent segments from the same physical build from appearing across the evaluation boundary. Five repeated specimen-level evaluations were performed to examine model consistency under different held-out specimens. Based on the experimental results, the following conclusions are reached:

- **Robust trajectory-informed raster-angle identification:** Integrating G-code trajectory descriptors with time-domain, directional, and wavelet-packet vibration features achieved 100% test accuracy across all five specimen-level evaluations, while vibration measurements independently demonstrated the ability to identify raster-angle states from physical process responses.
- **Complementary digital and physical side-channel information:** G-code trajectory features represent the commanded raster-angle state, whereas wireless vibration measurements capture the physical execution response, demonstrating complementary information pathways for AM side-channel monitoring and intrusion detection.
- **Specimen-level validation and model interpretability:** Specimen-level partitioning prevented train–test leakage and provided a more realistic assessment of generalization across unseen builds, while confusion matrices, feature-selection analysis, and t-SNE visualizations revealed class overlap and the contributions of trajectory and vibration information.

Future studies should extend the present framework toward direct command–execution verification by introducing controlled mismatches between the intended G-code and the physically executed process. The expected raster-angle state can then be compared with an independent vibration-based physical-state estimate to evaluate mismatch-detection sensitivity, false-alarm rate, detection confidence, and detection time. Future work should also increase the number of independent test specimens and adopt fully nested specimen-grouped cross-validation, with preprocessing, feature selection or PCA, and hyperparameter optimization refitted within each inner training fold. Additional experiments should examine different sensor placements, materials, print speeds, specimen geometries, nozzle conditions, and printer platforms to assess the robustness, transferability, and practical applicability of the framework for cyber-physical process monitoring and anomaly verification.

**Author's contributions:**

Methodology and conceptualization: Katherine Smith, Vukica Jovanović and Abdullah Al Mamun; Literature review and investigation: Angela Sicaja and Katherine Smith; Data collection: Angela Sicaja and Md Hedayetul Islam Chy; Manuscript drafting, MATLAB code implementation, and results analysis: Angela Sicaja and Md Hedayetul Islam Chy; manuscript review and supervision: Katherine Smith, Vukica Jovanović and Abdullah Al Mamun.

**Declaration of generative AI and AI-assisted technologies in the manuscript preparation process:**

During the preparation of this manuscript, the authors used ChatGPT to improve the language and readability of the manuscript. Following the use of this tool, the authors carefully reviewed and edited the content as necessary and took full responsibility for the final content of the published article.

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**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

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