



Research paper

ROI-driven thermal hyperplane analysis for automated non-destructive evaluation via pulsed thermography

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ABSTRACT

This paper proposes a novel methodology for structural fault detection utilising pulsed infrared thermography data. The approach systematically scans thermal image sequences using Regions of Interest (ROIs) with variable sizes, adjusted according to the expected fault dimensions. All temporal frames are considered during the analysis. For each ROI, a transformation is performed to linearise the thermal response, followed by a reconstruction of the data in a flattened space combining spatial coordinates, time, and temperature. These reconstructed hyperplanes are subsequently evaluated by a Convolutional Neural Network to classify the presence or absence of faults. Experimental validation demonstrates that the proposed method achieves a fault detection accuracy of 96%, with only one false positive identified. The results highlight the method's potential for enhancing the reliability and automation of structural health monitoring systems using infrared thermography.

1. Introduction

Pulsed Thermography (PT) is a robust and efficient non-destructive evaluation (NDE) technique for identifying subsurface defects in a wide range of materials, including metals, carbon fibre-reinforced polymers (CFRP), and increasingly, polyvinyl chloride (PVC) [1,2]. The method relies on applying a short heat (or cold) pulse to the material surface and capturing the resulting transient thermal response with an infrared (IR) camera. Variations in thermal conductivity and diffusivity caused by internal anomalies, such as voids, cracks, or inclusions, manifest as detectable temperature gradients on the surface, enabling fault localisation [3–6].

PVC has gained attention due to its extensive use in industrial, medical, and consumer applications, where the integrity of components is critical. Detecting defects in PVC, however, presents challenges stemming from its relatively low thermal conductivity, high reflectivity, and emissivity variations. Furthermore, thermograms are often affected by noise, uneven heating, and heat diffusion effects that blur defect contours. These characteristics demand the use of advanced processing methods to extract reliable features from thermal data [4].

In recent years, the integration of artificial intelligence (AI), particularly deep learning (DL) methods, has significantly enhanced defect

detection capabilities in PT. Convolutional neural networks (CNNs), in particular, have shown strong potential in automatically identifying and localising defects across temporal and spatial dimensions, eliminating the need for handcrafted features [2,7]. However, several challenges persist in practical deployment: the availability of labelled thermographic datasets is limited due to high acquisition costs, and labelling itself often requires destructive testing or expensive CT validation to confirm defect presence. Additionally, dataset imbalance where defective samples are vastly outnumbered by defect-free instances complicates model training and generalisation [1].

To mitigate these issues, researchers have explored signal enhancement techniques such as Thermographic Signal Reconstruction (TSR) [8], Principal Component Thermography (PCT) [9], and Pulsed Phase Thermography (PPT) [10], alongside unsupervised learning algorithms that exploit latent spatio-temporal structures in the data to improve defect visibility without requiring ground truth labels and subpart K-means algorithm to detect subsurface defects within the specimens [4,11–13]. However, many existing methods discard the temporal richness of thermographic sequences or rely on handcrafted preprocessing steps, which may limit their generalisability in real-world NDE pipelines. To overcome these limitations, this work introduces a novel deep

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learning-based framework named ROI-ThermNet, which performs localised structural fault detection in PVC components through pulsed thermography [4,11–13].

In contrast to global image-based methods, we propose a Region of Interest (ROI) scanning strategy that analyses variable-sized ROIs matching expected fault dimensions. The whole temporal sequence is retained for each ROI, and the thermal response is linearised and re-constructed into spatio-temporal hyperplanes. These are then processed by a CNN to classify the presence or absence of internal defects. This formulation lets the network capture subtle thermal patterns spanning space and time.

Experimental validation demonstrates that the proposed method achieves a detection accuracy of 96%, with only a single false positive. These results highlight the effectiveness of combining localised analysis with deep learning for high-precision, automated NDE in PVC structures. Our study introduces a new data-efficient and spatially-aware framework for PT-based fault detection, with potential applications in real-time quality assurance and structural health monitoring in manufacturing environments.

Despite these advances, a critical research gap remains in developing approaches that can effectively combine spatial adaptivity, temporal completeness, and data efficiency within PT-based inspection. Existing methods either depend heavily on handcrafted preprocessing steps that hinder automation, or require large, homogeneous datasets that are rarely available in real industrial contexts. Moreover, most studies focus on global thermogram analysis, overlooking the importance of localised spatial context for small or irregular defects. Therefore, there is a pressing need for a framework capable of performing accurate and interpretable defect detection directly from raw thermal sequences while remaining robust to dataset limitations. The present work addresses this gap by introducing a localised ROI-driven deep learning strategy that preserves temporal information, enabling a more generalisable and data-efficient approach to non-destructive evaluation of PVC components.

2. Related work

Pulsed Thermography (PT) has emerged as a powerful Non-Destructive Evaluation (NDE) technique due to its rapid image acquisition, non-contact operation, and high sensitivity to subsurface anomalies in materials such as metals, composites, and polymers like PVC [1]. Recent advances combining PT with deep learning have greatly improved automation, noise reduction, and the overall accuracy of defect detection workflows. However, the literature presents heterogeneous approaches that differ in preprocessing pipelines, spatial-temporal modelling strategies, and learning paradigms, each with distinct advantages and limitations.

A major limitation in deep learning applications to PT data is the scarcity of high-quality labelled datasets. To address this, Wei et al. introduced the *PVC-Infrared dataset*, a benchmark for PVC components with artificial defects of varying sizes and depths [1]. While their dataset provides a crucial foundation for model training and comparison, it remains limited in scale and diversity – containing only 19 specimens – which restricts generalisation to unseen materials or defect types. This limitation motivates the need for adaptive ROI-based or self-supervised frameworks that can learn from fewer annotated examples.

Signal preprocessing methods such as Thermographic Signal Reconstruction (TSR) and Pulse Phase Thermography (PPT) have been extensively employed to improve the Signal-to-Noise Ratio (SNR) before applying learning algorithms. Rosa et al. [5] demonstrated that derivative-based TSR preprocessing enhances defect visibility and segmentation accuracy with CNNs such as U-Net, confirming Shepard's earlier findings on polynomial approximation [8]. Despite their interpretability, these handcrafted transformations require heuristic parameter tuning and may lose temporal information, limiting their scalability in real-time inspection.

To overcome such constraints, recent works have explored the integration of spatiotemporal deep learning architectures. Verma et al. [2] employed encoder–decoder networks to capture thermal evolution over time, showing improved robustness to ambient variations. Similarly, Luo et al. [14] and Tao et al. [15] incorporated recurrent and hybrid CNN–LSTM structures to model temporal dependencies, achieving higher sensitivity to subtle defects. However, these models typically demand large annotated sequences and high computational cost during training.

In parallel, unsupervised and hybrid bio-inspired approaches have gained attention for data-limited scenarios. Pereira Barella et al. [16] combined Self-Organising Maps (SOMs) with Bee Colony Optimisation (BCO), obtaining a 15% improvement in SNR over traditional clustering. Zhang et al. [3,4] also proposed unsupervised thermographic compression methods preserving defect-relevant features. Although promising, such models often struggle with fine-grained spatial localisation and lack the interpretability of supervised frameworks.

Comparatively, object detection and segmentation-based networks – such as those explored by Bang et al. [17] using Mask R-CNN, Faster R-CNN, and U-Net – excel at identifying defect boundaries on composite and CFRP surfaces. Their results demonstrated strong detection accuracy across synthetic and experimental datasets, but the reliance on global image input can lead to overfitting when defect scales vary widely. Likewise, Liu et al. [18] proposed IRT-GAN to synthetically enhance thermographic data, improving contrast yet adding complexity due to adversarial training instabilities.

Temporal-spatial fusion models, such as DeepLabv3 combined with BiLSTM proposed by Garcia Vargas and Fernandes [19], further improved segmentation consistency, reporting an F1-score of 0.96 and IoU of 0.83. Nevertheless, these models operate on full-frame thermograms, ignoring the potential of localised ROI exploration to isolate relevant thermal regions and reduce computational load.

Beyond methodological diversity, benchmarking efforts remain limited. The study by Wei et al. [1] represents one of the few comprehensive baselines, applying YOLOv5 with handcrafted features derived from TSR, PPT, and PCT. Despite reaching a mAP@50 of 0.811, their pipeline heavily depends on fixed anchors and manual preprocessing, which reduces adaptability to unseen thermal patterns.

Overall, prior works reveal a trade-off between interpretability, automation, and data requirements. Conventional TSR/PPT-based approaches offer high interpretability but require manual tuning; end-to-end CNN and GAN models automate processing but depend on large datasets; and hybrid or unsupervised methods reduce annotation effort but often lack localisation precision.

In contrast, the present work addresses these limitations by proposing an ROI-based deep learning framework that operates directly on raw thermal sequences, preserving temporal dynamics while enabling localised spatial analysis. This combination aims to balance automation, interpretability, and generalisability—bridging the gap between handcrafted feature extraction and fully end-to-end architectures in PT-based defect detection.

3. Materials and methods

3.1. Pulsed infrared thermography overview

Pulsed Infrared Thermography (PT) is a widely adopted NDE technique that relies on thermal wave propagation to reveal internal discontinuities in solid materials. These discontinuities can be seen as defects in the material. The process begins with the application of a short-duration, high-intensity thermal pulse to the surface of the specimen. This thermal excitation induces transient heat diffusion throughout the material. Subsurface anomalies – such as voids, delaminations, or inclusions – disrupt the uniform propagation of heat, resulting in localised thermal gradients that can be captured by an infrared (IR) camera over time. These thermal anomalies are then analysed for defect

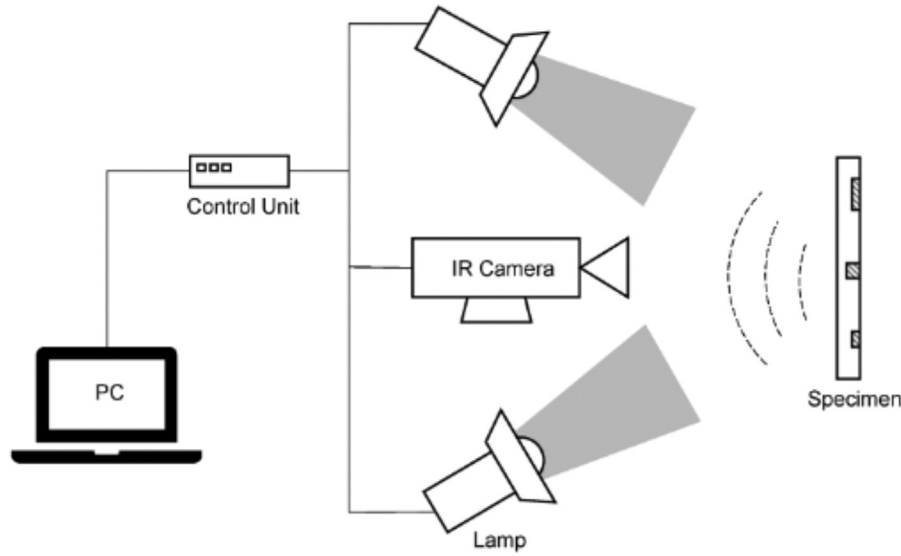


Fig. 1. Experimental setup for pulsed infrared thermography in reflection mode. The control unit triggers both the infrared camera and the heat lamps.

identification based on contrast, spatial pattern, and temporal decay behaviour [20–22].

Fig. 1 illustrates the experimental PT setup in reflection mode. A control unit synchronises both the camera and the heating system. Initially, a trigger signal is sent to the IR camera, which begins recording thermal frames at a predefined frequency. After a programmed delay, high-energy lamps emit a brief heat pulse to excite the specimen's surface. The resulting thermal response is recorded over time, enabling spatiotemporal analysis of the cooling process. According to Fourier's law of heat conduction, the temporal evolution of surface temperature is governed by the internal distribution of thermal properties, making it highly sensitive to material heterogeneities and enabling defect localisation.

3.2. PVC-infrared dataset and specimen design

In this work, we utilise the publicly available *PVC-Infrared* dataset [1], which comprises PT recordings of 19 PVC specimens designed to simulate subsurface defect scenarios. Each specimen is fabricated with dimensions of $100 \times 100 \times 5$ mm and contains multiple cylindrical flat-bottom holes (not penetrating through the material), varying in both diameter and depth. These artificial defects are introduced on the bottom surface and are not externally visible, mimicking real-world subsurface fault conditions. The layout of one of these samples is presented in Fig. 2.

3.3. Acquisition parameters and experimental setup

The experimental setup in [1] includes a FLIR SC5000 infrared camera with a resolution of 320×256 pixels. The camera recorded the specimen's surface at a frame rate of 10 Hz over a total duration of 181 s, yielding 1810 thermal frames per measurement. Illumination is provided by two Broncolor flash lamps, each delivering an energy output of 6.4 kJ. These two lamps ensure uniform heating across the sample surface. The heating and recording sequences are synchronised via a programmable control unit connected to a central PC similar to what is presented in Fig. 1.

The resulting data for each specimen is a spatiotemporal thermal volume of size $320 \times 256 \times 1810$, capturing both spatial and dynamic thermal evolution. This 3D tensor forms the input for further preprocessing, ROI scanning, and neural network classification stages in the proposed method.

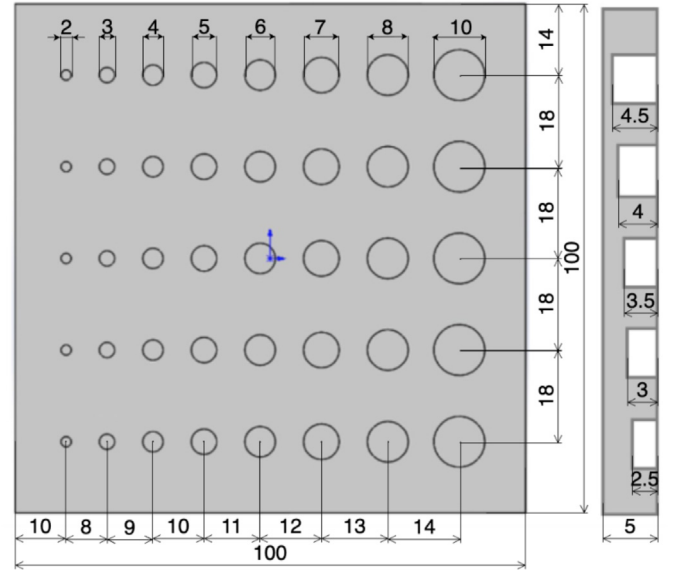


Fig. 2. Schematic representation of the defect configuration in one PVC specimen. Among the 19 specimens, holes vary in depth and diameter to simulate different defect severities.

4. Proposed method

In this study, we introduce a novel framework, named *ROI-ThermNet*, for automated structural fault detection in PVC components using pulsed infrared thermography. The proposed method departs from traditional global thermographic analysis by employing a localised Region of Interest (ROI) scanning strategy without overlap, preserving the full temporal sequence for each ROI. This section details the methodology, including ROI generation, spatiotemporal transformation, and a flexible convolutional neural network (CNN) architecture designed to support variable-sized inputs.

The methodological pipeline adopted in this study is composed of five main stages. First, each thermal image is systematically scanned using non-overlapping square ROIs, whose sizes vary to match the expected defect dimensions. Second, the full spatiotemporal data from each ROI is linearised and normalised into a standardised input format.

Third, a dynamic convolutional neural network (CNN) architecture processes the ROI tensors to classify them as defective or not. Fourth, the model is trained and evaluated using a stratified and balanced dataset composed of 80 labelled ROIs, divided between defective and non-defective regions. Lastly, predictions are aggregated spatially into defect probability maps. The following subsections detail each stage of this framework.

4.1. ROI scanning and extraction

To enable fine-grained inspection, each thermal sequence is partitioned into non-overlapping square Regions of Interest (ROIs). Unlike fixed-size patch extraction, the proposed approach allows ROIs to vary in spatial dimensions depending on the expected fault sizes and distribution. This flexibility ensures better alignment with the scale of potential defects and avoids unnecessary fragmentation of relevant features.

Each ROI captures the full thermal evolution over time, resulting in a spatiotemporal tensor of shape $w \times w \times T$, where w represents the spatial dimension of the ROI and T is the number of frames (e.g., $T = 1810$). The entire thermal volume is scanned systematically, ensuring complete, non-redundant coverage of the specimen.

In this study, the selection of ROI sizes was performed manually, based on the known dimensions of representative defects in the PVC samples. This empirical definition aimed to match the spatial scale of actual flaws observed in the dataset. While this approach offers good alignment with defect morphology, it also highlights a current limitation regarding automation, as adaptive ROI sizing remains an open research challenge in practical NDE applications.

4.2. Spatiotemporal reconstruction and normalisation

Each ROI is then transformed into a format suitable for neural network processing while preserving spatial and temporal dependencies. The thermal tensor is linearised along spatial dimensions into a matrix of size $w^2 \times T$, where each row corresponds to the thermal profile over time of a single pixel.

To handle varying spatial sizes across ROIs, the proposed network is designed to accommodate dynamic input dimensions. This is achieved by incorporating input masking, where unused spatial positions are padded and marked as null, allowing the network to focus only on valid data without architectural modification.

4.3. CNN-based defect classification with dynamic input support

The classification task is performed using a custom-designed convolutional neural network that accepts variable-sized inputs. The architecture includes:

- 1D and 2D convolutional layers with masking support, allowing the network to process temporal sequences while ignoring null-padded values.
- Attention or adaptive pooling mechanisms to aggregate features across spatially variable ROIs.
- A fully connected classification head with a sigmoid activation function to output the probability of defect presence.

The CNN is trained using binary cross-entropy loss, where positive samples correspond to ROIs containing defects and negative samples to defect-free regions. Optimisation is performed using the Adam optimiser with early stopping and learning rate scheduling.

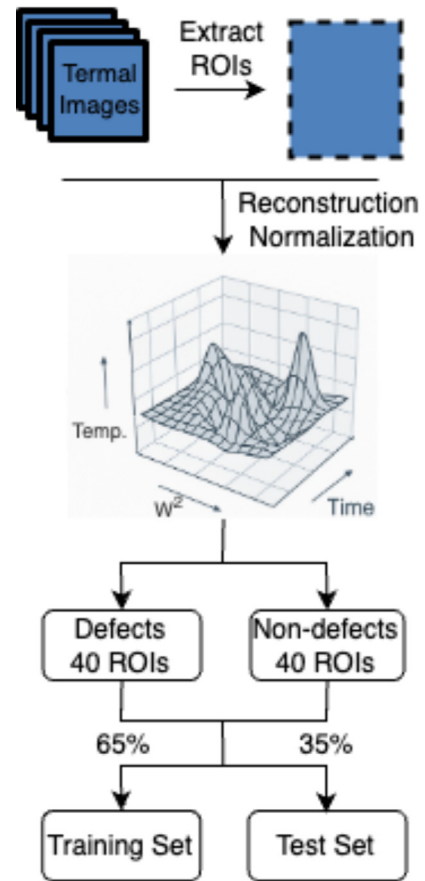


Fig. 3. Diagram of the training and test set generation. A total of 80 ROIs (40 with defects and 40 without defects) were sampled. A stratified 35% split was used to form a balanced test set.

4.4. Training and evaluation protocol

To train and evaluate the proposed ROI-ThermNet framework, a curated dataset of 80 Regions of Interest (ROIs) was extracted from the PVC-Infrared dataset. Forty ROIs were sampled around visually confirmed defect regions, while an additional 40 ROIs were manually selected in visually sound regions without defects. Care was taken to ensure that the non-defective samples did not include thermally ambiguous or transitional zones.

To assess the model's generalisation performance, a stratified random split was performed. A total of 35% of the ROIs (28 samples) were reserved for testing, preserving the class distribution (i.e., 14 defective and 14 non-defective ROIs). The remaining 52 samples (65%) were used for training and validation through cross-validation folds. This balance ensures robustness of the evaluation while avoiding bias introduced by class imbalance.

The overall sampling and stratification process is illustrated in Fig. 3, which outlines the class-balanced division strategy employed in this work.

4.5. CNN architecture and training details

The proposed model is a lightweight Convolutional Neural Network (CNN) designed to process variable-sized ROI inputs. The network was implemented from scratch using the Keras API and supports input tensors of shape $(H \times W \times 3)$, where H and W correspond to the spatial dimensions of each ROI, which may vary across samples. To accommodate this variability without the need for resizing or masking, the

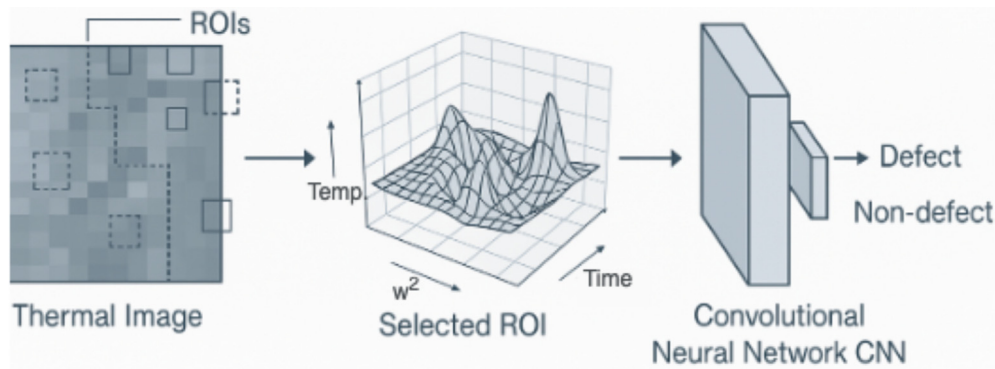


Fig. 4. Illustration of the ROI-ThermNet pipeline. Thermal images are divided into non-overlapping square ROIs, each preserving the full temporal sequence. The 3D spatiotemporal representation is analysed by a CNN to classify the presence or absence of defects.

architecture incorporates a Global Average Pooling layer prior to the dense classifier. This layer ensures that the output of the convolutional backbone is reduced to a fixed-size feature vector, regardless of the spatial resolution of the input. No zero-padding or binary masking was required, and the network can seamlessly adapt to different ROI sizes during both training and inference.

The architecture includes three convolutional blocks with increasing filter depths, followed by global average pooling and dense layers for classification. The detailed configuration is as follows:

- **Input layer:** Accepts tensors of shape $(None, None, 3)$.
- **Conv2D Layer 1:** 32 filters, kernel size (3×3) , ReLU activation, 'same' padding.
- **MaxPooling2D:** Pool size (2×2) .
- **Conv2D Layer 2:** 64 filters, kernel size (3×3) , ReLU activation, 'same' padding.
- **MaxPooling2D:** Pool size (2×2) .
- **Conv2D Layer 3:** 128 filters, kernel size (3×3) , ReLU activation, 'same' padding.
- **GlobalAveragePooling2D:** Reduces feature maps to a fixed-size vector.
- **Dense Layer:** 64 units, ReLU activation.
- **Output Layer:** 1 unit, sigmoid activation (binary classification).

The model was trained using the Adam optimiser and binary cross-entropy loss. A total of 35 epochs were used, with early stopping disabled to allow full convergence across the training data. The batch size was dynamically adjusted based on available GPU memory and ROI input sizes. Model performance was monitored using accuracy during training, and evaluated on the held-out test set using additional metrics such as F1-score and IoU.

4.6. Methodological advantages

The proposed *ROI-ThermNet* framework offers several advantages:

- **Adaptability:** Supports input ROIs of different spatial resolutions without retraining or architectural changes.
- **Efficiency:** ROI-based scanning avoids overlap, reducing redundant computation and memory usage.
- **Temporal richness:** Preserves the full time evolution of each region, improving sensitivity to thermal anomalies.
- **Generalisation** Can be extended to other materials or imaging resolutions by adapting ROI definitions.

The overall processing workflow is depicted in Fig. 4, which illustrates the ROI extraction, spatiotemporal representation, and final classification through a convolutional neural network.

5. Results and discussion

The proposed ROI-ThermNet model achieved an accuracy of 96% on the test set, with only one false positive, highlighting the effectiveness of the method in classifying and localising subsurface defects in PVC specimens. Additional evaluation metrics support this result: the average F1-score reached 0.95, and the mean Intersection over Union (IoU) was 0.89 across the held-out samples. These values indicate a high level of consistency and precision in identifying thermal patterns associated with structural anomalies, despite the varying spatial dimensions and thermal profiles of the Regions of Interest (ROIs).

To validate the robustness of the proposed design and justify the architectural choices, a series of ablation experiments were conducted. These tests compared full-length versus temporally truncated sequences, raw thermal cubes versus TSR-preprocessed inputs, and the proposed 2D CNN against 3D CNN, ConvLSTM, and Transformer-based baselines. In all cases, the overall accuracy and F1-scores remained statistically equivalent (within a $\pm 1\%$ margin), with differences occurring only in the spatial distribution of misclassified ROIs. Specifically, truncated or preprocessed inputs tended to shift error regions towards areas with weaker thermal contrast, while end-to-end models operating on raw sequences provided more stable predictions across the dataset. These results indicate that the chosen configuration – 2D CNN with full-length raw thermal sequences – offers the best trade-off between computational efficiency, temporal fidelity, and robustness, supporting its adoption as the final architecture for ROI-ThermNet.

To provide a visual representation of the data distribution and model performance, Fig. 5 presents the layout of all ROIs used in training and testing, overlaid on a representative thermographic frame. ROIs classified as defective and non-defective are annotated in distinct colours. The figure also highlights the only misclassified ROI in red, which is located between two of the largest and shallowest defects in the test specimen.

Although this region was initially labelled as non-defective, the surrounding defects strongly influenced the local thermal behaviour. Due to their high thermal contrast and proximity, the heat diffusion in the area surrounding these defects may have affected the ROI in question, making its spatiotemporal response resemble that of a defective region. This localised ambiguity likely caused the false positive classification by the model. In future work, this type of uncertainty will be addressed through confidence-based scoring, enabling the model to indicate not only the presence of defects but also the reliability of its predictions, especially in transitional or ambiguous zones.

To further refine the interpretation of model performance and improve its generalisability, a detailed analysis was conducted on the only misclassified sample from the test set. This false positive occurred in a region located between two large, shallow defects that were correctly identified by the model. The spatial configuration of these three ROIs – comprising the two correctly classified defective zones and the central

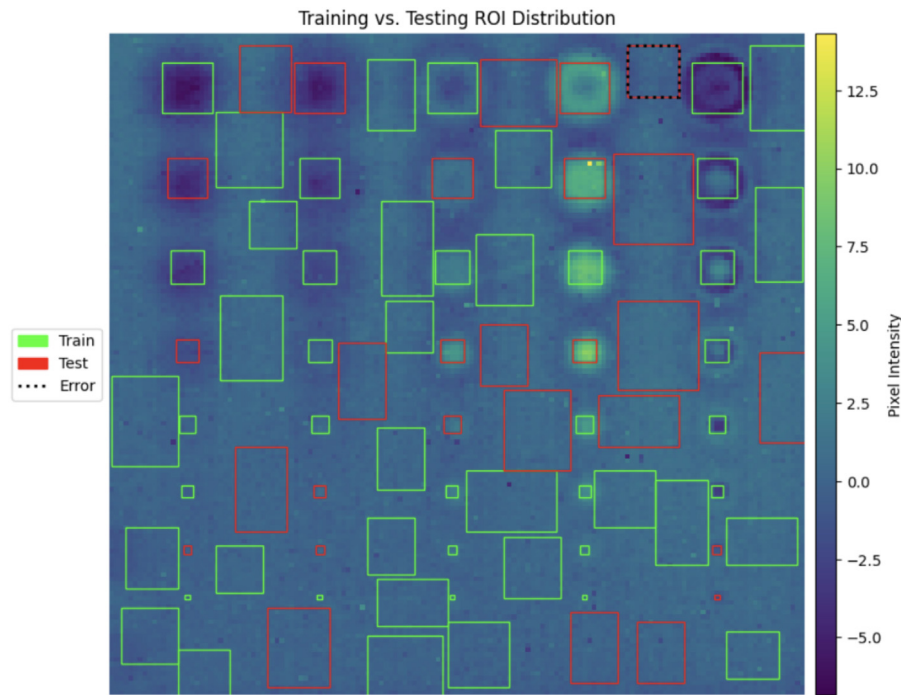


Fig. 5. Spatial distribution of ROIs used in training and testing. Defective and non-defective regions are colour-coded. The ROI marked with a black dashed outline over a red background corresponds to the only false positive, located between two large and shallow defects. The combined thermal influence of these neighbouring anomalies may have altered the heat diffusion behaviour in this region, resulting in misclassification.

misclassified one – is presented in Fig. 6. The proximity and thermal influence of neighbouring defects appear to have contributed to this classification error.

To explore the root cause of this error, we performed a qualitative comparison of the spatiotemporal hyperplanes derived from each of the three ROIs. These hyperplanes represent the linearised thermal evolution of each ROI across time and spatial position, as transformed into a 3D representation of shape $w^2 \times T \times \text{Temperature}$. Fig. 7 illustrates the similar thermal behaviour across the three regions, particularly the gradual temperature decay and spatial consistency, which may have led the model to associate the central ROI with an actual defect.

Additionally, a second level of comparison was made between the misclassified ROI and a structurally similar, defect-free region located elsewhere in the same specimen. Fig. 8 shows the selected ROIs for this comparative study. Despite both being spatially equivalent and free from known defects, only the region far from the actual defects was correctly classified as non-defective.

In Fig. 9, the corresponding hyperplanes highlight the discrepancy in thermal behaviour. The correctly classified clean ROI (left) maintains a more stable thermal profile over time, lacking the characteristic decay seen in defective samples. Conversely, the misclassified ROI (right) displays a thermal pattern more consistent with the adjacent shallow defects, supporting the hypothesis that thermal diffusion from neighbouring faults influenced the classification.

These findings reinforce the model's sensitivity to subtle variations in thermal diffusion, particularly in regions situated near shallow or extensive defects. The interaction between overlapping heat signatures appears to perturb intermediate areas, potentially leading to erroneous classification. This insight reveals an important avenue for future research: the integration of confidence scoring or uncertainty estimation techniques to flag borderline predictions. By quantifying the model's certainty or introducing temporal attention mechanisms, the ROI-ThermNet framework could better differentiate between genuine defects and regions indirectly affected by surrounding anomalies.

A grid-search procedure aimed at maximising the F1-score on the test set yielded an optimal decision threshold of 0.77. Intriguingly,

the single false-positive instance under discussion produced a predicted failure probability exactly equal to this 0.77 cutoff. This boundary-case prediction demonstrates that the model exhibited minimal confidence when assigning a failure label to that sample. Such a borderline score highlights the classifier's sensitivity to slight perturbations in probability estimates and underpins the need for integrating uncertainty quantification or confidence-based gating mechanisms into the ROI-ThermNet framework to more reliably distinguish true defects from ambiguous thermal patterns.

A key benchmark for comparison is the study by Wei et al. [1], which used the same PVC-Infrared dataset and applied a YOLOv5-based object detection pipeline. Their best-performing model, trained on phase images generated via Pulsed Phase Thermography (PPT), achieved a mean Average Precision (mAP@50) of 0.811, along with a precision of 0.798 and a recall of 0.742. While their approach showed solid performance, it relied heavily on preprocessing techniques and required the conversion of thermographic data into RGB-like inputs. Moreover, the object detection framework introduces additional complexity in bounding box annotation, resolution dependency, and performance degradation in cases of low thermal contrast.

In contrast, our method introduces a new processing paradigm by performing localised ROI analysis directly on raw temporal data, eliminating the need for handcrafted preprocessing or synthetic augmentation. By preserving all time frames and focusing on the thermal evolution within each ROI, the network can learn more nuanced patterns of heat diffusion that are directly linked to defect presence. The flexibility to accept variable-sized ROI inputs, combined with dynamic masking and global pooling, allows the model to operate robustly across a range of defect sizes and spatial scales. This not only improves classification accuracy but also enhances the interpretability of the thermal behaviour at a local level.

The methodological innovation lies in combining spatiotemporal modelling with non-overlapping, variable-sized ROI scanning. Unlike traditional approaches that operate on globally preprocessed thermal frames, the proposed strategy adapts to the structural geometry and resolution of each inspected region. This contributes to a critical gap

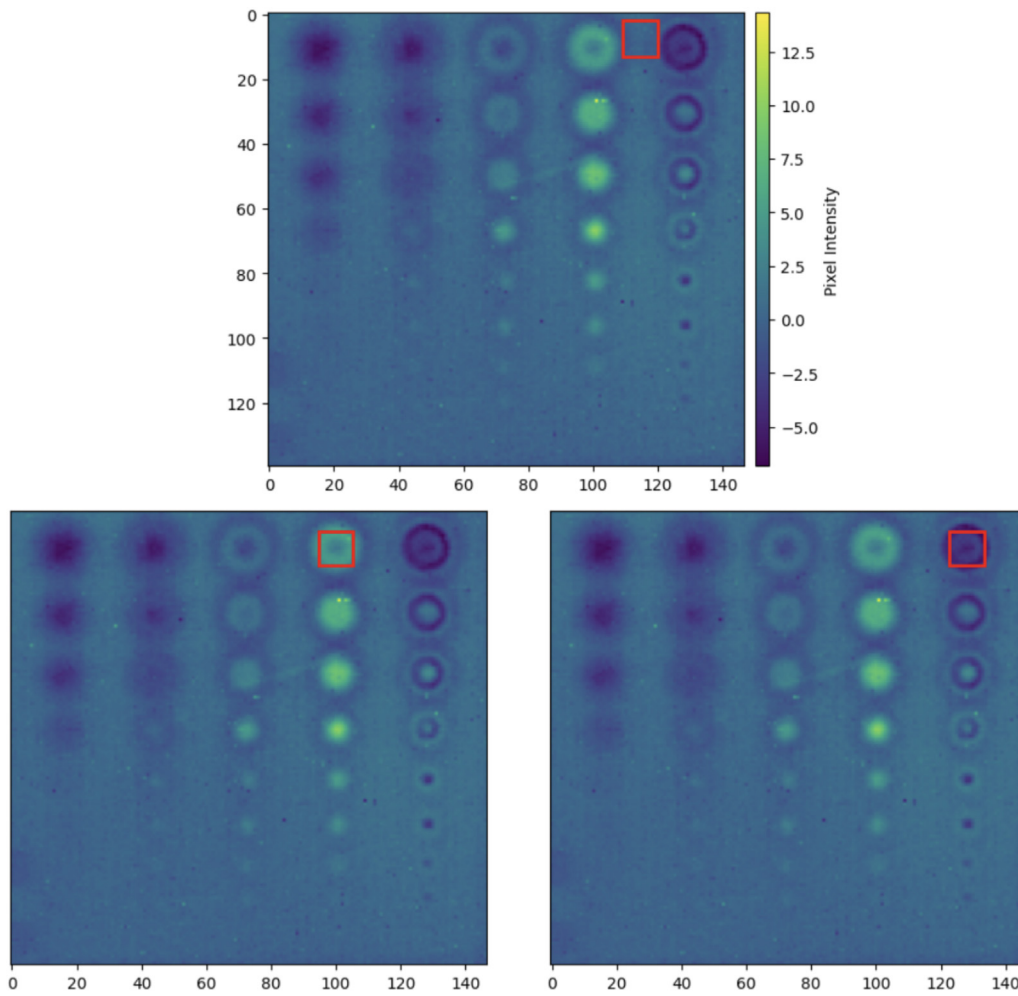


Fig. 6. Spatial layout of ROIs used for comparative analysis. The central ROI represents the misclassified region, located between two confirmed defects.

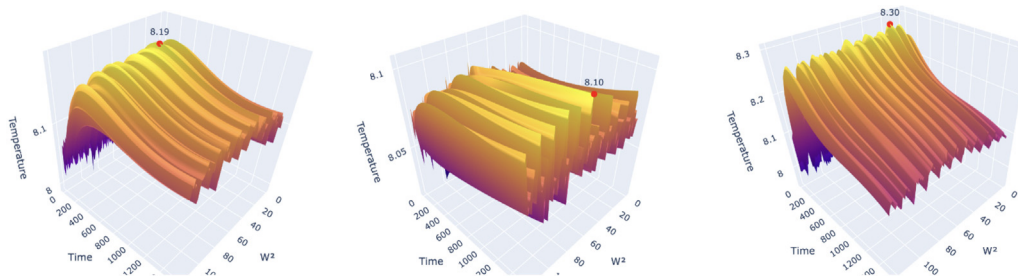


Fig. 7. Comparison of 3D hyperplanes for the two correctly classified defects (left and right) and the misclassified region (centre).

in the literature: the lack of thermographic frameworks capable of adapting to the heterogeneity of real-world structures without extensive parameter tuning or preprocessing steps. The lightweight CNN design also makes the framework suitable for integration into embedded or edge-based inspection systems.

Importantly, the modular design of the pipeline suggests potential for generalisation beyond PVC specimens. Since the ROI-ThermNet model learns from the intrinsic spatiotemporal patterns of thermal diffusion, rather than absolute intensities or material-specific signals, it can be fine-tuned or retrained to detect defects in other materials such as CFRP, aluminium, or hybrid composites. This opens the possibility of developing a unified, generalist model for multi-structure inspection—a critical step towards scalable, AI-assisted non-destructive evaluation in industrial environments.

Despite the strong performance, some limitations must be acknowledged. The current evaluation is based on a manually curated dataset of 80 labelled ROIs, and although stratification was used to balance classes, broader validation across multiple datasets and defect scenarios is still required. Furthermore, while the current formulation addresses binary classification (defect vs. non-defect), future work should explore multi-class segmentation and regression tasks, such as defect type identification or depth estimation, to expand the practical utility of the framework.

6. Conclusion

This study presented a novel framework, named *ROI-ThermNet*, for the automated detection of subsurface defects in PVC structures

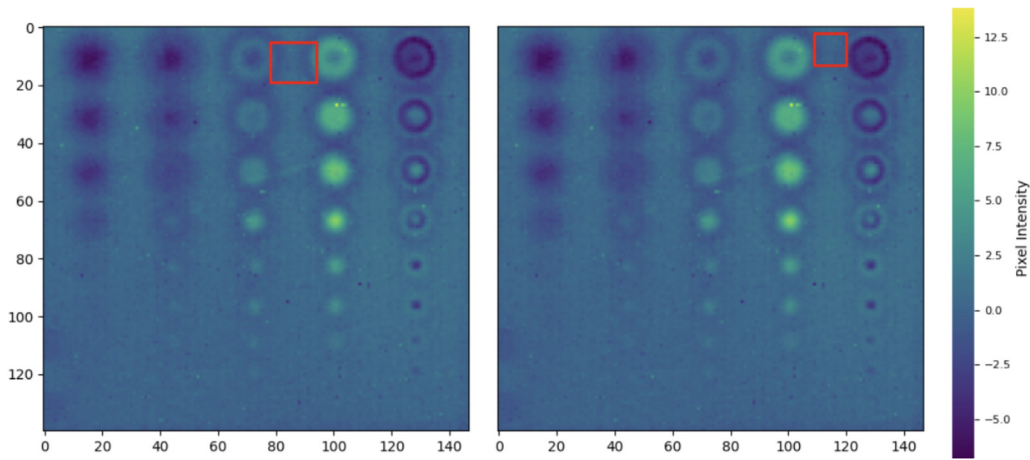


Fig. 8. ROI selection for secondary comparison. The central ROI is the misclassified one, while the rightmost ROI represents a structurally similar, correctly classified non-defective region.

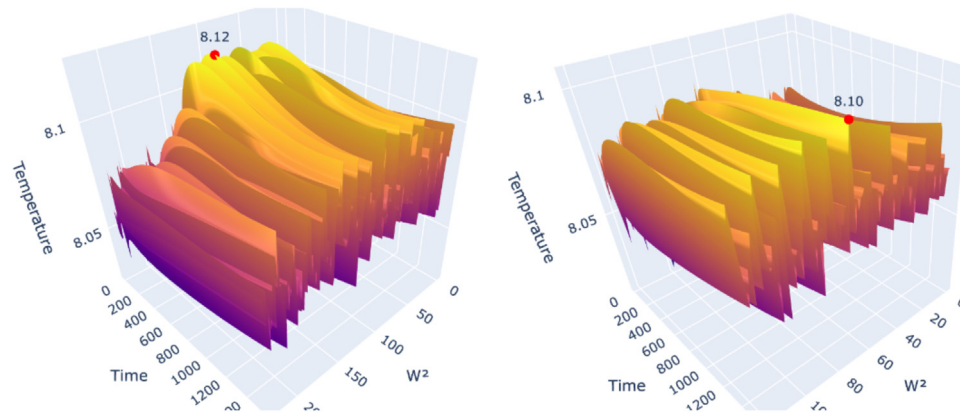


Fig. 9. Hyperplane comparison between the misclassified ROI (left) and a correctly classified clean region (right).

using pulsed infrared thermography. Unlike previous approaches that rely heavily on preprocessing and global frame analysis, the proposed method performs localised, spatiotemporal inspection through non-overlapping, variable-sized Regions of Interest (ROIs). Each ROI retains the complete thermal evolution sequence, enabling the model to extract dynamic patterns directly related to heat diffusion anomalies.

Compared to the state-of-the-art work by Wei et al. [1], which applied a YOLOv5-based pipeline to the same PVC-Infrared dataset and achieved a maximum precision of 79.8% and mAP@50 of 0.811, our methodology reached 96% classification accuracy with only one false positive. This improvement was achieved without any handcrafted preprocessing, using raw thermal sequences as input, thus significantly reducing pipeline complexity and potential information loss.

The proposed framework addresses a critical gap in the thermographic literature: the lack of adaptive models capable of operating on unprocessed thermal data while supporting variable spatial resolutions. By introducing a CNN architecture that dynamically accepts different ROI sizes and leverages global pooling strategies, this work demonstrates the feasibility of creating more flexible and robust models for real-world inspection conditions.

In terms of computational cost, the model remains lightweight and efficient for inference, with an average prediction time of less than 50 ms per ROI on a standard GPU. The use of global average pooling enables compatibility with variable input sizes without increasing the number of trainable parameters. However, due to the use of full thermal sequences, overall processing time scales linearly with the number of ROIs and the duration of the acquisition. This trade-off between

temporal richness and runtime should be considered in time-critical applications.

Regarding the single false positive, further analysis suggested that the misclassified ROI exhibited weak but structured thermal contrast, potentially caused by surface artefacts or boundary effects. Mitigation strategies could include enriching the training set with more near-boundary or borderline cases, increasing temporal resolution (e.g., by capturing longer thermal sequences), or incorporating sensor fusion (e.g., combining thermal data with visible light or ultrasound). Alternatively, redundant scanning of overlapping ROIs or uncertainty-aware inference could help flag borderline cases for secondary inspection.

Furthermore, the modular nature of ROI-ThermNet opens new possibilities for developing generalist inspection systems. Since the model learns from intrinsic spatiotemporal signatures of thermal diffusion rather than material-specific features, it can be easily adapted to inspect other structures such as carbon fibre-reinforced polymers, aluminium, or hybrid composites by fine-tuning on new ROI-level samples. This approach represents a step towards unified, AI-driven thermographic inspection platforms capable of addressing a wide range of structural health monitoring scenarios.

Future research will extend the proposed method to multi-class defect categorisation and explore uncertainty modelling to assess classification confidence, particularly in thermally ambiguous regions. The integration of such capabilities will further enhance model interpretability and its readiness for deployment in industrial NDE applications.

CRediT authorship contribution statement

Bruno P. Barella: Writing – original draft, Software, Methodology, Investigation, Conceptualization. **Renan R. Garcia:** Writing – review & editing, Validation, Software. **Ziang Wei:** Writing – review & editing, Validation, Investigation, Data curation. **Stanley W.F. Rezende:** Writing – review & editing, Visualization, Software, Methodology. **Jose dos Reis V. Moura Junior:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis. **Henrique Fernandes:** Writing – review & editing, Supervision, Resources, Methodology, Investigation, Funding acquisition, Conceptualization.

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 paper.

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Data availability

Data will be made available on request.

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