

Automated Neutron Dosimetry with Bubble Detectors Using CNN-Based Object Detection

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Abstract

Bubble detectors are widely used for measuring neutron yields in nuclear fusion and various neutron sources, as well as in monitoring personal neutron radiation dose. The neutron yield or radiation dose is typically quantified by counting the bubbles formed within the detector. However, manually counting a high density of bubbles in high-neutron-yield experiments is not only labor-intensive and time-consuming but also prone to subjective bias and errors. Furthermore, conventional threshold-based image processing algorithms face challenges in resolving issues related to bubble occlusion and overlapping, limiting their accuracy in high-density bubble scenarios. To address these challenges, an automated neutron dosimetry system that employs Convolutional Neural Network (CNN)-based object detection and a multi-view tracking algorithm has been developed. This system automates bubble quantification while minimizing counting discrepancies arising from bubble occlusion and overlapping in three-dimensional volumes. Notably, the automated counts achieved relative accuracies exceeding 95% when compared to expert manual counts on the independent test set. By capturing multi-angle imagery and performing cross-view tracking, the system effectively identifies bubbles occluded in single-perspective views. This automated framework significantly improves the precision, efficiency, and reliability of neutron dosimetry across diverse applications, including nuclear fusion, various neutron sources, and radiation protection, etc.

Full Text

Preamble

Automated Neutron Dosimetry with Bubble Detectors Using CNN-Based Object Detection* Xin-yan Li,¹ De-bin Zou,¹ † Yan-qing Deng,² Chao-zhi Li,¹

Wei Qi,³ Shu-kai He,³ Bo Cui,³ Kai-yuan Feng,¹ Chen Xie,¹ Jin-long Luo,¹ Li-xiang Hu,¹ Jie Feng,¹ Fu-qiu Shao,¹ and Tong-pu Yu^{1, ‡} ¹College of Science, National University of Defense Technology, Changsha 410073, China ²College of Advanced Interdisciplinary Studies, National University of Defense Technology, Changsha 410073, China ³Science and Technology on Plasma Physics Laboratory, Laser Fusion Research Center, China Academy of Engineering Physics, Mianyang 621900, China Bubble detectors are widely used for measuring neutron yields in nuclear fusion and various neutron sources, as well as in monitoring personal neutron radiation dose. The neutron yield or radiation dose is typically quantified by counting the bubbles formed within the detector. However, manually counting a high density of bubbles in high-neutron-yield experiments is not only labor-intensive and time-consuming but also prone to subjective bias and errors. Furthermore, conventional threshold-based image processing algorithms face challenges in resolving issues related to bubble occlusion and overlapping, limiting their accuracy in high-density bubble scenarios. To address these challenges, an automated neutron dosimetry system that employs Convolutional Neural Network (CNN)-based object detection and a multi-view tracking algorithm has been developed. This system automates bubble quantification while minimizing counting discrepancies arising from bubble occlusion and overlapping in three-dimensional volumes. Notably, the automated counts achieved relative accuracies exceeding 95% when compared to expert manual counts on the independent test set. By capturing multi-angle imagery and performing cross-view tracking, the system effectively identifies bubbles occluded in single-perspective views. This automated framework significantly improves the precision, efficiency, and reliability of neutron dosimetry across diverse applications, including nuclear fusion, various neutron sources, and radiation protection, etc.

Keywords: Neutron dosimetry, Bubble detector, Convolutional neural network, Object detection, Multi-object tracking.

INTRODUCTION

Neutrons are electrically neutral particles characterized by strong penetrating capability and are extensively utilized in non-destructive testing (NDT) [1-3], neutron resonance spectroscopy [4, 5], nuclear astrophysics [6, 7], and nuclear medicine [8, 9]. Moreover, neutron yield serves as a fundamental quantitative metric across a broad range of applications, from evaluating the key parameter-energy gain factor (Q)-in nuclear fusion [10, 11], to quantifying neutron source characteristics in spallation neutron source [12, 13], and further to assessing radiation fields and calibrating dosimetry for shielding design and radiation protection [14-16]. Consequently, accurate characterization of neutron fields, together with precise quantification of neutron dose, is therefore essential for nuclear fusion performance evaluation, radiation safety, and a wide range of neutron-based scientific and industrial applications.

Conventional neutron dosimetry predominantly relies on activation foils [17, 18],

neutron time-of-flight (nTOF) spectrometers [19, 20], and bubble detectors. Bubble detectors, in particular, offer high sensitivity, low detection threshold, stable response across a broad neutron-energy spectrum, and inherent insensitivity to gamma radiation. Consequently, they are widely used as a standard measurement method for neutron-yield characterization in nuclear fusion [21, 22] and * This work is supported by the National Natural Science Foundation of China (Grant No. 12275356) and the Natural Science Foundation of Hunan Province of China (Grant No. 2025JJ30002). † Corresponding author, debinzou@nudt.edu.cn ‡ Corresponding author, tongpu@nudt.edu.cn have also been extensively applied in laser-driven neutron sources [23–28]. Moreover, bubble detectors are recognized as the only personal neutron dosimeters that provide an energy response fully compliant with International Commission on Radiological Protection (ICRP) 60 recommendations [29], making them indispensable for individual radiation monitoring. The bubble detector contains superheated droplets (such as Freon-12 [29]) suspended within an elastic gel matrix [30].

Upon neutron irradiation, the droplets vaporize to form visible bubbles, the number of which is directly proportional to the received neutron dose, enabling direct readout of dose by counting the number of bubbles. However, converting this visual information into accurate quantitative data remains a significant challenge. The traditional method of manual counting is labor-intensive, time-consuming, and prone to subjective errors, particularly in high-neutron-yield experiments where hundreds of bubbles may form within a single detector.

To automate the readout process, various computer vision techniques have been proposed and investigated extensively [31–33]. While traditional algorithms based on intensity thresholding or edge detection perform adequately for sparsely distributed bubbles, they frequently fail in complex, high-bubble-density experiment scenarios. Beyond algorithmic constraints, the hardware configuration for image acquisition also presents intrinsic limitations. In a standard single-perspective imaging setup, the spatial distribution of bubbles across varying depths is collapsed onto a single image plane through projection, inevitably causing partial overlap or total occlusion. Such geometric interference precludes conventional algorithms from accurately resolving and quantifying individual bubbles, resulting in loss of spatial information and leading to a systematic underestimation of the incident neutron dose. Fig. 1 [FIGURE:1]. (Color online) Schematic illustration of the proposed method for automated neutron dose measurement. Upon neutron irradiation, visible bubbles form within the detector. The bubble detector can be rotated to capture images from multiple viewpoints. Bubbles are detected in each image using a convolutional neural network (CNN)-based object detection model. Cross-view tracking links identical bubbles across views to eliminate duplicate counting, while incrementing the count for newly detected bubbles. The neutron dose is ultimately derived from the total number of unique bubbles identified. tron dose.

The evolution of deep learning, particularly regarding Convolutional Neural Network (CNN)-based object detection models, has demonstrated exceptional

capabilities in extracting information from complex experimental data [34]. In the broader context of nuclear science, machine learning techniques have been increasingly adopted to address challenges that are difficult for conventional methods, ranging from the parametrization of resolution functions in neutron facilities [35] and the prediction of fundamental nuclear properties [36] to super-resolution neutron imaging [37]. Specific to imaging-based diagnostics, these methodologies have been successfully implemented in diverse tasks, including particle track recognition in CR39 nuclear track detectors [38, 39], the automated characterization of irradiation-induced defects in nuclear materials [40, 41], machine learning-based track reconstruction in diffusion cloud chambers [42], and rare event classification in Active Target Time Projection Chambers (AT-TPCs) [43]. However, despite these advancements, the application of such advanced AI techniques to the automatic identification of bubbles in bubble detectors remains, to the best of our knowledge, totally unexplored in current literature.

In this study, we developed an automated neutron dosimetry system that synergizes deep learning with a multi-view tracking strategy [44, 45]. We incorporated a fine-tuned object detection model to facilitate rapid and robust bubble identification. Crucially, to mitigate bubble-to-bubble occlusion in high-density environments, we engineered a rotary hardware platform to capture the multi-angle imagery of bubble detectors. This is coupled with a cross-view tracking algorithm designed to correlate bubble identities across multiple perspectives, thereby effectively recovering bubbles that are occluded in single views. Furthermore, an integrated Optical Character Recognition (OCR) module automatically extracts detector serial numbers for association with bubble counts, enabling fully automated radiation dose calculation. This end-to-end framework substantially enhances the precision, efficiency, and reliability of neutron dosimetry, offering a robust solution to high-throughput neutron radiation diagnostics.

The remainder of this paper is organized as follows. Section II details the methods, including the system overview, data processing pipeline, bubble detection network, dataset preparation, and model training. Section III presents the results, covering model performance metrics, independent test set evaluation, and multi-view bubble tracking for dosimetry.

Finally, Section IV concludes with key findings, and future directions.

II. METHODS

A. System overview and data processing pipeline

To automate the readout process of the neutron dose in bubble detectors, an integrated, automated readout system was developed, which synchronizes a motor-driven rotation stage with high-resolution image acquisition. A key feature of the system is the motorized rotation stage, which allows precise rotation of the bubble detector at predefined angles for a specified number of rotations. The bubble detector is placed between the light source and the camera, with image acquisition synchronized to the motorized rotation stage under back-lighting conditions, enabling auto-

Figure 2

Figure 1: Figure 2

mated capture from multiple viewing angles. A lens with a high f-number was selected to provide an extended depth of field, ensuring sharp focus on bubbles across varying depths in detector and yielding high-quality images for subsequent automated bubble counting.

The schematic overview of the proposed automated neu- Fig. 2

. (Color online) Overview of the automated data processing pipeline for a single bubble detector image. The workflow comprises ROI segmentation, parallel bubble detection via a fine-tuned bubble detection model, and serial number extraction through OCR, enabling automated data association for each detector. The neutron dose measurement method is shown in Fig. 1. After neutron irradiation, visible bubbles form within the detector, and the neutron dose is quantitatively proportional to the number of bubbles generated. During rotation, the same bubble may appear in multiple images. Additionally, certain bubbles may be partially or completely occluded in some views, rendering them visible only from specific angles. To address the limitations of single-view imaging, the detector should be rotated to capture images from multiple viewpoints, as shown in Fig 1.

Bubbles in each image are automatically detected using a CNN-based object detection model, which is described in detail in the following subsection. To prevent duplicate counting across views, a cross-view tracking algorithm is implemented to associate identical bubbles across different images. This enables differentiation between newly detected bubbles and those previously identified, with only new bubbles incrementally added to the total count while tracked bubbles excluded.

The neutron dose is then calculated from the total number of unique bubbles using the detector's calibrated sensitivity and the corresponding conversion formula [46, 47]. This multi-view fusion and tracking approach ensures precise determination of each bubble count, from which the neutron dose can be accurately derived.

An overview of the automated data processing pipeline for a single bubble detector image is depicted in Fig. 2. The input raw image is initially segmented into two distinct regions of interest (ROIs), with the experimental region containing the bubbles and the label region containing the serial number.

Bubble detection is executed by a fine-tuned bubble detection model (detailed architecture is shown in Fig. 3 [FIGURE:3]), which outputs bounding boxes for individual bubbles. In parallel, OCR is applied to the label region to automatically extract the detector's unique serial number. This dual-branch architecture enables linkage of the bubble count to the unique serial number

of the respective detector—corresponding to its calibrated sensitivity—thus allowing automated computation of the neutron dose.

B. Bubble detection network Accurate detection of neutron-induced bubbles presents a challenging computer vision problem, as bubbles typically appear as small size, dense distribution, or partially overlapping within a gel background. To address these issues, we adopt YOLOv11 (You Only Look Once, version 11) [48, 49], a recently proposed one-stage object detection framework that demonstrates strong performance in dense and small-object detection scenarios while maintaining high inference efficiency.

The detailed architecture of the YOLOv11 model used for bubble detection is depicted in Fig. 3. YOLOv11 incorporates an enhanced backbone and neck, improving feature extraction and multi-scale representation. The backbone utilizes cascaded C3k2 blocks (Cross Stage Partial with kernel size 2), retains the Spatial Pyramid Pooling-Fast (SPPF) layer, and integrates a Cross Stage Partial with Spatial Attention (C2PSA) module. These elements facilitate extraction of rich, detailed features and effective focus on salient regions.

In practice, this configuration markedly improves detection of small, densely packed objects. The C2PSA attention mechanism prioritizes critical areas, enhancing accuracy for minute or partially occluded bubbles. The multi-scale neck fuses features across levels via successive upsampling, concatenation, and additional C3k2 blocks, thereby improving localization of small targets. The detection head utilizes additional C3k2 blocks and convolutional layers to produce predictions at three scales, ultimately generating bounding boxes for the detected bubbles. This structure is particularly advantageous for small-target detection tasks involving bubbles in bubble detectors.

C. Dataset The performance of deep learning models, particularly CNN, is intrinsically linked to the quality of the training data.

Fig. 3. (Color online) Detailed architecture of the fine-tuned bubble detection model. The input image first passes through the backbone network, which extracts multi-scale features via convolutional layers and specialized modules including C3k2, SPPF, and C2PSA. These features are then integrated in the neck through upsampling, concatenation, and additional C3k2 blocks. Finally, the detection head further processes the fused features through several C3k2 blocks and outputs bounding boxes on the original detector image.

A robust and well-annotated dataset serves as the cornerstone for the model to learn representative features and achieve high generalization capability. In the context of neutron dosimetry, where bubble overlapping and varying background noise can significantly affect counting accuracy, high-fidelity data is a prerequisite for reliable automated detection.

Guided by this principle, high-quality images of the bubble detectors were acquired from laser-driven neutron source experiments conducted at the Xing-Guang III laser facility [50].

The dataset contains a wide range of bubble densities, varying from sparse distributions to dense clusters, which is critical for training the bubble detection model to handle complex In total, 212 high-quality raw images were collected.

Accurate ground truth data is paramount for model training. To mitigate human error and subjective bias, a "double-check" procedure was implemented. Initial annotations were performed by researchers and subsequently verified by senior experts with extensive experience in manual bubble counting.

Any ambiguous instances were reviewed to ensure the reliability of the dataset.

The annotated dataset was split into training, validation, and testing subsets in an approximate ratio of 85:13:2 to facilitate model training and objective evaluation. A dedicated testing set consisting of 5 representative images was reserved for independent testing. These images were withheld from both training and validation to permit direct comparison between manual bubble counts and model predictions, thereby evaluating the model's performance against that of human experts. The detailed distribution of the dataset is presented in Table 1.

TABLE 1. Distribution of the neutron bubble detector image dataset.

Percentage (%) Subset Training Validation Testing Total Number of Images performance computing platforms. Detailed hardware and software specifications are summarized in Table 2. Training results indicate that the proposed model achieves superior computational efficiency during both the training and Specifically, a 100-epoch training cycle is completed within approximately 30 minutes, with the model reaching convergence within 40 epochs. Quantitative performance metrics are detailed in the following section III A. Such minimal computational overhead and rapid convergence characteristics not only underscore the efficiency of the methodology and the appropriateness of the bubble detection model architecture but also demonstrate the feasibility of the model training on consumer-level hardware. This enhanced accessibility significantly lowers the technical barrier to entry, facilitating continuous model iteration and streamlining future retraining procedures.

TABLE 2. Hardware and software configuration used for the network training.

Category Computing Hardware Specification GPU Model GPU Memory PyTorch Python Version / Details RTX 4090 Laptop

16 GB

D. Model training Deep Learning Framework Programming Environment The model training and evaluation were executed on a local consumer-grade laptop, without recourse to high- III. RESULTS were also considered. Precision and recall are defined as:

A. Model Performance To ensure reliable neutron dose quantification, the bubble detection model must demonstrate both high localization accuracy and robust generalization capabilities. We monitored the training process by analyzing loss functions and performance metrics, as illustrated in Fig. 4 [FIGURE:4]. All curves presented here were smoothed using a moving average window of five epochs to suppress short-term fluctuations and highlight underlying trends.

The training losses, specifically the Box loss and Distribution Focal Loss (DFL), are shown in Fig. 4(a) and (b). The Box loss quantifies the error in the predicted bounding box coordinates (x, y, width, height) relative to the ground truth, serving as a direct indicator of localization precision. The DFL allows the model to learn a probability distribution for each bounding box coordinate rather than a single point estimate. This is particularly crucial for precise localization of bubbles with diffuse or blurred edges within the gel. Both loss curves exhibit a steady decline and achieve convergence after approximately 40 epochs. This rapid convergence indicates that the bubble detection network efficiently learns the morphological features of the bubbles without suffering from vanishing gradients or optimization instability.

Specifically, the Box loss decreases from about 2 and stabilizes around 1, while the DFL converges to approximately

1.1. It is worth noting that, unlike simple mean-squared error

(MSE), the specific loss functions employed in the YOLO architecture (based on Intersection over Union and probability distribution entropy) typically converge to a stable non-zero value rather than zero [38]. The convergence profile and final converged loss value demonstrate that the model effectively minimizes the prediction errors within a modest number of training epochs.

To comprehensively evaluate the detection accuracy, we utilized the mean Average Precision (mAP), which serves as the standard metric for quantifying object detection performance. The mAP is defined as the mean value of the Average Precision (AP) across all object classes (in this case, the single class of “bubble”). AP is defined as the area under the precision-recall (P-R) curve (with the corresponding precision and recall curves presented in Fig. 5 [FIGURE:5]), quantifying the model’s ability to sustain high precision across varying recall levels. Mathematically, the AP and mAP are expressed as follows: (cid:90) $AP = \int_{0}^{1} Precision(Recall)d(Recall)$ mAP = (cid:88) $AP = \frac{TP}{TP + FP}$ Recall = $\frac{TP}{TP + FN}$ and the F1 Score is defined as:

$F1\ Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$ Here, TP (true positive) denotes instances of correctly detected bubbles, FP (false positive) corresponds to noise (e.g., dust or gel artifacts) mistakenly detected as bubbles, and FN (false negative) indicates actual bubbles overlooked by the model (i.e., missed detections). High precision signifies a low false detection rate, whereas high recall indicates a low missed detection rate.

We analyzed two specific metrics: mAP0.5 and mAP0.5:0.95. The former measures accuracy when the Intersection over Union (IoU) threshold is set to 0.5, representing a lenient criterion suitable for general counting. The latter averages the mAP over a range of IoU thresholds from 0.5 to 0.95, imposing a stringent criterion that demands high geometric alignment between the predicted box and the ground truth. As depicted in Fig. 4(c), the mAP curves demonstrate a robust learning trajectory. The mAP0.5 curve starts from approximately 0.2 and exhibits a rapid ascent, stabilizing after epoch 40. Notably, the final stabilized value approaches 1.0, indicating that the model achieves near-perfect detection performance under standard overlap criteria. This result is critical for neutron dosimetry, as it ensures that virtually every visible bubble is correctly identified and counted, directly minimizing errors in dose calculation.

Furthermore, the stricter metric, mAP0.5:0.95, stabilizes at a high value of approximately 0.8. This exceptionally high score demonstrates the precise localization of the predicted bounding boxes. Such high detection performance provides a solid foundation for the subsequent multi-view tracking and accurate quantification of neutron radiation dose.

As shown in Fig. 5, all three metrics—precision, recall, and F1—exhibit a rapid rise during the initial training stages, followed by a stable plateau. The model converges to stable performance after approximately 30 training epochs, with an average precision exceeding 0.97 and recall above 0.95 in the final training stage. This results in a corresponding F1 Score of approximately 0.96. This behavior demonstrates that the model possesses a high learning rate and quickly adapts to the feature space of the bubble dataset. The final converged values (indicated by dashed horizontal lines in Fig. 5) confirm that the model achieves a high degree of detection reliability.

These results validate the bubble detection model as a robust tool for automated bubble counting.

Independent test set evaluation where N is the number of classes (here $N = 1$ for bubbles).

In addition to mAP, the standard metrics of precision, recall, and F1 Score (the harmonic mean of precision and recall) To rigorously assess the practical efficacy of the trained bubble detection model and compare its performance against Fig. 4. (Color online) Training curves of the bubble detection model. (a) Box loss and (b) DFL for the training and validation sets. (c) mAP at IoU thresholds of 0.5 and 0.5-0.95. All curves are smoothed using a moving average window of 5 epochs to suppress short-term fluctuations. The losses decrease steadily and converge after approximately 40 epochs, while the mAP curves gradually increase and stabilize, indicating a stable training process and good generalization performance of the bubble detection model.

Fig. 5. (Color online) Evolution of the detection performance during training. (a) Precision, (b) Recall, and (c) F1 score of the bubble detection model. The dashed horizontal lines denote the final averaged values after convergence.

All curves are smoothed using a moving average window of 5 epochs. The rapid rise of the metrics in the early stage and the subsequent stable plateau demonstrate fast convergence and stable detection performance of the bubble detection model. manual counting, systematic evaluations were conducted on an independent test set comprising five images reserved exclusively for this purpose. These images were withheld from both training and validation phases, ensuring an unbiased estimation of model performance.

For each test image, manual bubble counting was performed by an experienced experimenter with extensive expertise in visual inspection of bubble detectors. These manual counts served as the ground truth for benchmarking the model's predictive accuracy.

A comparison of the model's automated counts with manual results is presented in Table 3. Across all test images, the automated and manual counts exhibited excellent agreement, with relative accuracies ranging from 95% to 100%. These results demonstrate that the trained bubble detection model reliably identifies and counts neutron-induced bubbles under realistic experimental imaging conditions.

C. Multi-view bubble tracking Although single-view detection exhibits high accuracy, the three-dimensional distribution of bubbles within the gel renders single-view imaging insufficient, inevitably resulting in missed detections (TABLE 3). Comparison between manual counting and model-based bubble counting Image Manual Counting Model Counting Accuracy Fig. 6 [FIGURE:6]. (Color online) Demonstration of multi-view bubble tracking for improved counting accuracy. (a) Original image (top) and detection result (bottom) from a single view of a bubble detector tube, with detected bubbles labeled by unique serial numbers and color-coded for tracking. A region of interest (red box) containing overlapping and partially occluded bubbles is highlighted. (b) Magnified views of the selected region from three different angles (View-1, View-2, and View-3). A constant angular separation of 1° is maintained between adjacent views. Bubbles visible across multiple views retain consistent numbering and coloring (e.g., #31- #35). Notably, bubble #39 is invisible in View-1 due to occlusion but becomes clearly visible in View-2 and View-3 (indicated by red arrows), where it is newly assigned and counted, illustrating the advantage of multi-view tracking in reducing missed detections.

In cases of underestimation of the neutron dose. high-neutron-yield experiment, where bubble density is elevated significantly, mutual occlusion among bubbles becomes Fig. 7 [FIGURE:7]. (Color online) Quantitative evaluation of counting accuracy.

The bar chart compares the results from four static views against the proposed multi-view bubble tracking strategy. The red dashed line represents the expert-verified ground truth (39 bubbles). For each bar, the absolute count and the corresponding relative accuracy are displayed. The proposed method achieves 100% accuracy, whereas static views exhibit fluctuating underestimations. prevalent.

To mitigate this limitation, multi-object tracking is applied across multi-view images of the same detector, enabling cross-view association and unique identification of individual bubbles.

To clearly illustrate the effectiveness of the proposed multi-view tracking strategy, Fig. 6 presents a representative set of carefully selected data in which significant bubble occlusion occurs. Fig. 6(a) presents a representative detection result from a single view, where the algorithm successfully identifies the visible bubbles. To elucidate the tracking mechanism, a specific ROI characterized by the overlapping bubbles is analyzed across three distinct rotation angles (View-1, View-2, and View-3), as detailed in Fig. 6(b). Each viewpoint is separated by a precise angular increment of 1° . The advantage of rotation is highlighted by the detection of bubble #39. Bubble #39 is spatially occluded by the foreground bubble #32, rendering it undetectable by static image processing method.

However, as the detector rotates to View-2 and View-3, the parallax shift reveals the previously hidden bubble #39. The system immediately recognizes this as a new object, assigns it a unique ID #39.

Multi-view bubble tracking was implemented using the ByteTrack algorithm [51]. A key feature of ByteTrack is its retention and utilization of nearly all detected bounding boxes, without discarding low-confidence candidates.

This approach is particularly effective for tracking partially occluded bubbles, which typically exhibit lower detection scores. The tracking algorithm assigns a unique ID to each detected bubble and preserves this ID across consecutive views by leveraging spatial trajectory continuity and feature matching. As observed in the ROI, bubbles labeled #31 through #35 remain clearly visible across all three views. The system successfully associates these detections, maintaining consistent ID assignment and color coding, thereby preventing duplicate counting of the same bubble despite the change in perspective.

Detected bubbles that cannot be associated with any existing trajectory are considered newly appearing bubbles, and a new ID is generated by incrementing the current maximum assigned bubble ID by one. During the processing of images acquired from consecutive views, the final bubble count produced by the multi-view bubble tracking algorithm is determined by the maximum assigned bubble ID.

For the data illustrated in Fig. 6, Fig. 7 provides a quantitative comparison between the counts produced by the proposed multi-view bubble tracking strategy and those obtained from each individual static view. As summarized in Fig. 7, the counting accuracy for individual static views (View-0 to View-3) fluctuated between 92% and 97%. These variations confirm that static 2D projections are highly sensitive to the orientation of bubble detectors, often failing to resolve occluded objects.

In contrast, the proposed multi-view bubble tracking strategy successfully

synthesized the information from the entire rotation sequence, achieving a final count of 39 with 100% accuracy for this detector. This result demonstrates that the integration of multi-angle imagery effectively restores lost information, providing a more reliable and robust solution for high-precision neutron dosimetry.

- IV. CONCLUSION In summary, we have developed and validated an automated neutron dosimetry system that synergizes mechanical [1] X. Li, B. Li, Y. Wang et al., A nondestructive method based on absorption of polychromatic neutron beam for monitoring internal gas of sealed container. *Nuclear Analysis* 4 (2), 100173 (2025). doi: 10.1016/j.nucana.2025.100173. [2] S. Wang, C. Cao, W. Yin et al., A Novel NDT Scanning System Based on Line Array Fast Neutron Detector and D-T Neutron Source. *Materials* 15 (14), 4946 (2022). doi: 10.3390/ma15144946. [3] M. Inês Silva, E. Malitckii, T. G. Santos et al., Review of conventional and advanced non-destructive testing techniques for detection and characterization of small-scale defects. *Progress in Materials Science* 138, 101155 (2023). doi: 10.1016/j.pmatsci.2023.101155. [4] J. Feng, J. Ren, H. Xu et al., Proof-of-principle demonstration of epithermal neutron resonance spectroscopy utilizing a compact laser-driven electron accelerator. *Proceedings of the National Academy of Sciences* 122 (40), e2518397122 (2025). doi: 10.1073/pnas.2518397122. [5] D.-X. Wang, S.-Y.-L.-T. Zhang, W. Jiang et al., Resonance analysis of $^{159}\text{Tb}(n, \gamma)$ reaction based on the CSNS Back-n experiment. *Nuclear Science and Techniques* 36 (3), 43 (2025). doi: 10.1007/s41365-024-01617-9. [6] W.-P. Liu, B. Guo, Z. An et al., Recent progress in nuclear astrophysics research and its astrophysical implications at the China Institute of Atomic Energy. *Nuclear Science and Techniques* 35 (12), 311 (2024). doi: 10.1007/s41365-024-01590-3. [7] M. S. Smith, Nuclear data resources and initiatives for nuclear rotation, CNN-based object detection, and multi-view object tracking. This study addresses the longstanding challenges in neutron yield measurement using bubble detectors, specifically the labor-intensive nature of manual counting and the systematic errors introduced by bubble occlusion in high-bubble-density scenarios.

By developing a bubble detection model, we achieved robust bubble identification with a mAP0.5 approaching 1.0 and an F1 score of 0.96. The model demonstrates excellent generalization capabilities, maintaining high accuracy on independent test sets comparable to expert manual assessment. Furthermore, the integration of a rotary hardware platform with a cross-view tracking algorithm successfully resolves the issue of overlapping bubbles. As evidenced by the multi-view tracking results, the system effectively distinguishes between identical bubbles across changing viewpoints and recovers bubbles occluded in single-perspective images, ensuring a precise bubble count. The combination of an OCR module with the bubble detection model further streamlines the workflow. This module directly associates the physical measurements with the pre-stored calibrated sensitivity of the corresponding detector, enabling au-

tomated neutron dose computation and establishing a direct linkage between the bubble counts and the neutron yield.

This fully automated framework significantly enhances the efficiency, reliability, and reproducibility of neutron dosimetry. It offers a practical solution for large-scale data analysis in laser fusion experiments, laser-driven neutron source characterization, and routine radiation protection monitoring, paving the way for high-throughput neutron diagnostics. *Frontiers in Astronomy and Space Sciences* 10, 1243615 (2023). doi: 10.3389/fspas.2023.1243615. [8] J. Cai, Y. Zhu, X. Zhu et al., Recent advances in coordination chemistry on the application and development of radiopharmaceuticals and boron neutron capture therapy.

Coordination Chemistry Reviews 551, 217448 (2026). doi: 10.1016/j.ccr.2025.217448.

[9] K. L. Batani, M. R. D. Rodrigues, A. Bonasera et al., Generation of radioisotopes for medical applications using high-repetition, high-intensity lasers. *High Power Laser Science and Engineering* 13, e83 (2025). doi: 10.1017/hpl.2024.92.

[10] J. D. Kilkenny, A. Pak, O. L. Landen et al., The crucial role of diagnostics in achieving ignition on the National Ignition Facility (NIF). *Physics of Plasmas* 31 (8), 080501 (2024). doi: 10.1063/5.0211684. [11] A. B. Zylstra, O. A. Hurricane, D. A. Callahan et al., Burning plasma achieved in inertial fusion.

Nature 601 (7894), 542-548 (2022). doi: 10.1038/s41586-021-04281-w. [12] D. Chiesa, C. Cazzaniga, M. Nastasi et al., Measurements of neutron fields in a wide energy range using multi-foil activation analysis. *IEEE Transactions on Nuclear Science* 69, 1659-1666 (2022). doi: 10.1109/TNS.2021.3138636 [13] D. Chiesa, M. Nastasi, C. Cazzaniga et al., Measurement of the neutron flux at spallation sources using multi-foil activation. *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment* 902, 14-24 (2018). doi: 10.1016/j.nima.2018.06.016

[14] P. Saengkaew and K. Ploykrachang, Comprehensive review of neutron techniques, detection, and dosimetry in science and technology. *Discover Applied Sciences* (2026). doi: 10.1007/s42452-025-08024-8 [15] J. M. Gomez-Ros, R. Bedogni, C. Domingo, Personal neutron dosimetry:

State-of-the-art and new technologies. *Radiation Measurements* 161, 106908 (2023). doi: 10.1016/j.radmeas.2023.106908. [16] M. Fragopoulou, S. Stoulos, M. Manolopoulou et al., Dose measurements around spallation neutron sources. *Radiation Protection Dosimetry* 132, 277-282 (2008). doi: 10.1093/rpd/ncn280

[17] D. L. Bleuel, C. B. Yeaman, L. A. Bernstein et al., Neutron activation diagnostics at the National Ignition Facility (invited).

Review of Scientific Instruments 83 (10), 10D313 (2012). doi: 10.1063/1.4733741. [18] M. A. Mangan, C. L. Ruiz, G. W. Cooper et al., Inferring neutron yields using indium activation samples for small fractions of tritium added to deuterium fuel in inertial confinement fusion (ICF) experiments. *Review of Scientific Instruments* 93 (10), 103537 (2022). doi: 10.1063/5.0101823. [19] X. Su, P. Zhou, J. L. Li et al., Calibration of a gated neutron time-of-flight spectrometer with low-afterglow. *Review of Scientific Instruments* 96 (9),

103537 (2022). doi: 10.1063/5.0101823. [19] X. Su, P. Zhou, J. L. Li et al., Calibration of a gated neutron time-of-flight spectrometer with low-afterglow. *Review of Scientific Instruments* 96 (9),

103537 (2022). doi: 10.1063/5.0101823. [19] X. Su, P. Zhou, J. L. Li et al., Calibration of a gated neutron time-of-flight spectrometer with low-afterglow. *Review of Scientific Instruments* 96 (9),

103537 (2022). doi: 10.1063/5.0101823. [19] X. Su, P. Zhou, J. L. Li et al., Calibration of a gated neutron time-of-flight spectrometer with low-afterglow. *Review of Scientific Instruments* 96 (9),

103537 (2022). doi: 10.1063/5.0101823. [19] X. Su, P. Zhou, J. L. Li et al., Calibration of a gated neutron time-of-flight spectrometer with low-afterglow. *Review of Scientific Instruments* 96 (9),

103537 (2022). doi: 10.1063/5.0101823. [19] X. Su, P. Zhou, J. L. Li et al., Calibration of a gated neutron time-of-flight spectrometer with low-afterglow. *Review of Scientific Instruments* 96 (9),

103537 (2022). doi: 10.1063/5.0101823. [19] X. Su, P. Zhou, J. L. Li et al., Calibration of a gated neutron time-of-flight spectrometer with low-afterglow. *Review of Scientific Instruments* 96 (9),

103537 (2022). doi: 10.1063/5.0101823. [19] X. Su, P. Zhou, J. L. Li et al., Calibration of a gated neutron time-of-flight spectrometer with low-afterglow. *Review of Scientific Instruments* 96 (9),

103537 (2022). doi: 10.1063/5.0101823. [19] X. Su, P. Zhou, J. L. Li et al., Calibration of a gated neutron time-of-flight spectrometer with low-afterglow. *Review of Scientific Instruments* 96 (9),

103537 (2022). doi: 10.1063/5.0101823. [19] X. Su, P. Zhou, J. L. Li et al., Calibration of a gated neutron time-of-flight spectrometer with low-afterglow. *Review of Scientific Instruments* 96 (9),

103537 (2022). doi: 10.1063/5.0101823. [19] X. Su, P. Zhou, J. L. Li et al., Calibration of a gated neutron time-of-flight spectrometer with low-afterglow. *Review of Scientific Instruments* 96 (9),

093302 (2025). doi: 10.1063/5.0242176. [20] A. S. Moore, D. J. Schlossberg, B. D. Appelbe et al., Neutron time of flight (nToF) detectors for inertial fusion experiments.

Review of Scientific Instruments 94 (6), 061101 (2023). doi: 10.1063/5.0133655. [21] B. M. Knight, C. M. Gautam, C. R. Stoner et al., Detailed characterization of kHz-rate laser-driven fusion at a thin liquid sheet with a neutron detection suite. High Power Laser Science and Engineering 12, e46 (2023). doi: 10.1017/hpl.2023.84. [22] M. Gherendi, V. L. Zoita, T. Craciunescu et al., Neutron field parameter measurements on the JET tokamak by means of super-heated fluid detectors. Review of Scientific Instruments 83 (10), 10D915 (2012). doi: 10.1063/1.4739410. [23] S. Vallieres, F. Fillion-Gourdeau, S. Fourmaux et al., High average-flux laser-driven neutron source. Nature Communications 16, 97 (2025). doi: 10.1038/s41467-025-66535-9. [24] R. Lelievre, W. Yao, T. Waltenspiel et al., A comprehensive characterization of the neutron fields produced by the Apollon petawatt laser. The European Physical Journal Plus 139 (11), 1166 (2024). doi: 10.1140/epjp/s13360-024-05679-x. [25] D. Jung, K. Falk, N. Guler et al., Characterization of a novel, short pulse laser-driven neutron source. Physics of Plasmas 20, 056706 (2013). doi: 10.1063/1.4804640 [26] Y. Arikawa, M. Utsugi, M. Alessio et al., High-Intensity Neutron Generation via Laser-Driven Photonuclear Reaction. Plasma and Fusion Research 10, 2404003 (2015). doi: 10.1585/pfr.10.2404003 [27] I. Pomerantz, E. McCary, A. R. Meadows et al., Ultrashort pulsed neutron source. Physical Review Letters 113, 184801 (2014). doi: 10.1103/PhysRevLett.113.184801 [28] Y. L. Yao, S. K. He, Z. Lei et al., High-Flux Neutron Generator Based on Laser-Driven Collisionless Shock Acceleration. Physical Review Letters 131, 025101 (2023). doi: 10.1103/PhysRevLett.131.025101 [29] G. Zhang, B. Ni, L. Li et al., Study on bubble detectors used as personal neutron dosimeters. Applied Radiation and Isotopes 69 (10), 1453-1458 (2011). doi: 10.1016/j.apradiso.2011.05.008. [30] Bubble Technology Industries Inc. (2025). Bubble Technology Industries. <https://bubbletech.ca/>. [31] B. Thamocharan, B. Venkatraman, A. Anusuya et al., Analysis of various edge detection techniques for dosimeter bubble detector images. Biomedical Research 28 (20), 8701-8705 (2017). www.biomedres.info. [32] M. Birjukovs, P. Trtik, A. Kaestner et al., Resolving Gas Bubbles Ascending in Liquid Metal from Low-SNR Neutron Radiography Images. Applied Sciences 11 (20), 9710 (2021). doi: 10.3390/app11209710. [33] P.-W. Huang, Y.-C. Zane Wang, F.-C. Wang, Real-Time bubble counting for sensing petroleum valve closure leakage. Measurement 227, 114221 (2024). doi: 10.1016/j.measurement.2024.114221. [34] A. A. Murat and M. S. Kiran, A comprehensive review on YOLO versions for object detection. Engineering Science and Technology, an International Journal 70, 102161 (2025). doi: 10.1016/j.jestch.2025.102161 [35] P. Zugec, M. Sabat'e-Gilarte, M. Bacak et al., Machine learning based parametrization of the resolution function for the first experimental area of the nTOF facility at CERN. Nuclear Science and Techniques 36 (2025). doi: 10.1007/s41365-025-01820-2 [36] Z.-P. Gao, Y.-J.

Wang, H.-L. L'ü et al., Machine learning the nuclear mass. *Nuclear Science and Techniques* 32, 109 (2021). doi: 10.1007/s41365-021-00956-1 [37] Y.-H. Ma, B. Tang, W. Yin et al., Single-neutron super-resolution imaging based on neutron capture event detection and reconstruction. *Nuclear Science and Techniques* 36, 114 (2025). doi: 10.1007/s41365-025-01668-6 [38] Y. Wang, A. X. Chen, M. Salazar et al., Deuterium-deuterium fusion charged particle detection using CR-39 and deep learning model. *Radiation Measurements* 185, 107444 (2025). doi: 10.1016/j.radmeas.2025.107444. [39] G. Amit, N. Guy-Ron, O. Even-Chen et al., Deep learning-based alpha particles spectroscopy with solid-state nuclear track detector CR-39. *Radiation Measurements* 179, 107326 (2024). doi: 10.1016/j.radmeas.2024.107326. [40] C. M. Anderson, tomated Detection X-750. *Ultramicroscopy* 10.1016/j.ultramic.2020.113068.

J. Klein, H. Rajakumar et al., Au-Irradiated of Helium Bubbles (2020). [41] K. Burns, K. Tadj, T. Allaparti et al., Deep learning-enabled probing of irradiation-induced defects in time-series micrographs. *APL Machine Learning* 2 (1), 016106 (2024). doi: 10.1063/5.0186046. [42] N. J. Muller, D. Porawski, L. Wilde et al., Neuro-explicit semantic segmentation of the diffusion cloud chamber. *Review of Scientific Instruments* 94 (6), 063302 (2023). doi: 10.1063/5.0109284. [43] P. Dey, A. K. Anthony, C. Hunt et al., Point-cloud based machine learning for classifying rare events in the Active-Target Time Projection Chamber. *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment* 1072, 170002 (2025). doi: 10.1016/j.nima.2024.170002. [44] X.Y. Li, D.B. Zou, T.P. Yu, Neutron bubble detector counting device. *Chinese Patent* (2025). CN 223092149 U [45] X.Y. Li, D.B. Zou, and T.P. Yu, Method, system, medium, and program product for counting neutron bubble detectors, *Chinese Patent Application* CN 121385964A (2025). [46] L. Zhao, M.-H. Xu, Y.-H. Zhang et al., Laser fast neutron measured by bubble detector. *Acta Physica Sinica* 67 (22), 225202 (2018). doi: 10.7498/aps.67.20181035. [47] A. Kleinschmidt, V. Bagnoud, O. Deppert et al., Intense, directed neutron beams from a laser-driven neutron source at PHELIX. *Physics of Plasmas* 25 (5), 053101 (2018). doi: 10.1063/1.5006613. [48] J. Redmon, S. Divvala, R. Girshick et al., You Only Look Once:

Unified, Real-Time Object Detection. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

IEEE, 779-788 (2016). doi: 10.1109/CVPR.2016.91. [49] M. H. Rahima Khanam, YOLOv11: An overview of the key architectural enhancements. *arXiv preprint* (2024). doi: 10.48550/arXiv.2410.17725 [50] Y. Wu, B. Zhu, K. Dong et al., XingGuang III laser facility and its experimental ability to drive high-energy particle beams. *Laser Physics* 30, 096001 (2020). doi: 10.1088/1555-6611/aba3ca [51] Y. Zhang, P. Sun, Y. Jiang et al., ByteTrack: Multi-object tracking by associating every detection box. *arXiv preprint* (2022). doi: 10.48550/arXiv.2110.06864

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