



Comparative study of bubble segmentation methods for image analysis in hydrogen-based fluidized beds

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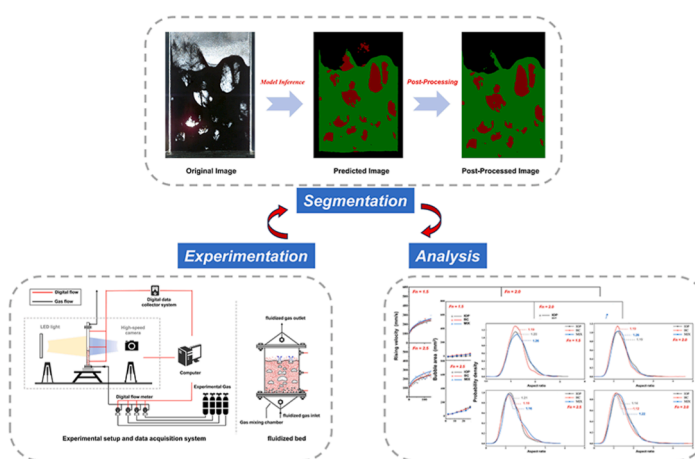
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HIGHLIGHTS

- DeepLabV3+ framework is developed for simultaneous gas–solid phase segmentation in iron ore powder fluidization.
- Segmentation accuracy and efficiency of DeepLabV3+ with different backbone networks are systematically evaluated.
- The method is compared with threshold-based approaches and the SAM3 foundation model.
- Fluidization behaviors of different particles under various conditions are analyzed using the proposed method.

GRAPHICAL ABSTRACT



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ABSTRACT

Clarifying the fluidization behavior of iron ore powders in fluidized beds is a fundamental issue for realizing hydrogen-based fluidized bed reduction. Digital image analysis (DIA), as a promising non-intrusive diagnostic technique, provides an effective approach for the quantitative characterization of fluidization behavior. In this study, a DeepLabV3+-based deep learning framework was employed to simultaneously segment the gas and solid phases during the fluidization process, and the effects of different backbone network configurations on training cost and segmentation performance were systematically evaluated. On this basis, the proposed method was further compared with conventional threshold-based segmentation methods and the general-purpose foundation model SAM3. The results indicate that using ResNet18 as the backbone achieves a favorable balance between segmentation accuracy and computational efficiency. The deep learning-based segmentation method shows strong adaptability to complex backgrounds and diverse fluidization states, and its segmentation accuracy and processing efficiency are significantly superior to those of traditional image segmentation methods and SAM3. Further experimental results based on this approach reveal that, at the same fluidization number, the iron ore powder system generates smaller bubbles with lower rising velocities, exhibiting a bubble population characterized by smaller sizes, higher number density, and lower rising velocities. With increasing hydrogen

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concentration in the fluidizing gas, the bubble size decreases further and the bed expansion ratio is reduced, while the variations in bubble shape and rising velocity remain insignificant.

1. Introduction

Under the pressure of the “Dual-Carbon” targets and the implementation of the EU Carbon Border Adjustment Mechanism (CBAM), China's iron and steel industry is facing an urgent need to accelerate its transition toward green and low-carbon development (Shahabuddin et al., 2023; Yu & Tan, 2022; Zhang et al., 2021, 2023). Hydrogen-based fluidized bed reduction has attracted increasing attention in recent years, as it enables the direct reduction of iron ore fines, thereby eliminating sintering and pelletizing pretreatment steps, simplifying the process flow, reducing production costs, and offering excellent heat and mass transfer characteristics (Bhaskar et al., 2020; Liu et al., 2021; Sun et al., 2023; Wolfinger et al., 2022). In the context of hydrogen fluidized bed metallurgy, iron ore fines exhibit significantly higher particle density than commonly used industrial particles (e.g., FCC catalysts and quartz sand), and can therefore be classified as typical high-density particles. Previous studies have shown that high-density particles often exhibit fluidization behaviors that differ markedly from those of conventional particles (Jiang, Qiu, et al., 2024; Li et al., 2023, 2024; Liu et al., 2015; Zhou et al., 2023). Accordingly, the specific fluidization behavior of iron ore fines in hydrogen-based fluidized beds remains of considerable research interest.

The selection of appropriate gas–solid flow diagnostic techniques is essential for investigating fluidization behavior. At present, gas–solid flow measurement techniques for fluidized beds can generally be classified into intrusive and non-intrusive methods. Intrusive techniques typically obtain flow information by installing sensors within the flow field; however, the presence of such probes inevitably disturbs the original flow structure to some extent (Turton, 2008). In contrast, non-intrusive techniques—such as digital image analysis (DIA), electrical capacitance tomography (ECT), particle image velocimetry (PIV), and positron emission particle tracking (PEPT)—allow gas–solid flow information to be acquired without perturbing the flow field. Among these techniques, DIA has been widely adopted in recent years due to its ability to directly capture rich flow-structure information (Sun & Yan, 2016; Wang & Yang, 2020; Zhang et al., 2014).

DIA is commonly combined with quasi-two-dimensional fluidized beds and high-speed imaging systems and has been extensively applied to the investigation of bubble and cluster evolution mechanisms (Li et al., 2020; Shen et al., 2004; Zhu et al., 2024). When using DIA to analyze flow behavior, a critical prerequisite is the accurate identification and separation of gas–solid flow structures from recorded images, which essentially constitutes an image segmentation problem. Traditional image segmentation approaches mainly include threshold-based methods, edge detection, clustering techniques, and graph-based segmentation methods, among which threshold-based segmentation has been most widely applied in gas–solid flow studies. Early threshold-based segmentation methods generally rely on empirically selected fixed threshold values (Bai et al., 2022; Busciglio & Vella, 2009; Zhu et al., 2023). However, the main limitation of fixed-threshold methods lies in their poor generalization capability: a single threshold is typically effective only under conditions with clear foreground–background contrast and performs poorly in complex scenes involving multiple targets. In gas–solid flow imaging, strong phase mixing, together with unavoidable variations in illumination and imaging conditions, often leads to significant segmentation errors, which can adversely affect the reliability of subsequent quantitative analysis. To address these limitations, adaptive thresholding techniques have been introduced into gas–solid flow detection, among which the Otsu thresholding method (also known as the maximum inter-class variance method) (Otsu, 1975) is the most representative, as it automatically

determines an optimal threshold based on the grayscale distribution of the image. Zhou et al. applied the Otsu method to quantitatively analyze bubble behavior in a fluidized bed of Geldart Group C+ particles with nano-additives, demonstrating its effectiveness in identifying bubble structures in complex high-density particulate systems (Zhou et al., 2021). Cano-Pleite et al. further proposed a double threshold segmentation strategy combining fixed and adaptive thresholds, enabling a more refined characterization of solids holdup and bubble dynamics in vibrated fluidized beds with different Geldart particle classifications (Cano-Pleite et al., 2016).

With the development of deep learning techniques, computer vision-based segmentation methods have gradually been introduced into gas–solid flow research. By training on labeled datasets, these methods are capable of achieving accurate segmentation of target structures in complex scenes under specific operating conditions. Jiang et al. employed a U-Net architecture to investigate bubble behavior in an air–glass bead bubbling fluidized bed (Jiang, Wu, et al., 2024); Fu et al. analyzed single-bubble dynamics in a fluidized bed using the DeepLabV3+ framework and achieved highly accurate segmentation results (Chen et al., 2018a, 2018b; Fu et al., 2024); Peng et al. compared U-Net and DeepLabV3 architectures, demonstrating that DeepLabV3 provides superior segmentation accuracy, whereas U-Net achieves comparable accuracy with higher inference efficiency (Yang et al., 2024). Nevertheless, these studies mainly focused on the identification of the bubble phase, while the solid-phase structure was not explicitly distinguished, despite its importance for understanding gas–solid flow mechanisms, and a comprehensive comparison among different segmentation approaches is still lacking.

In recent years, advances in foundation vision models have led to the emergence of general-purpose visual segmentation frameworks, among which the Segment Anything Model (SAM) is a representative example. The primary advantage of SAM lies in its ability to perform high-quality segmentation of diverse targets without task-specific retraining, relying instead on prompt-based guidance (Carion et al., 2025; Kirillov et al., 2023; Ravi et al., 2024). The SAM framework has now evolved to its third generation (SAM3) (Carion et al., 2025) and has begun to be applied in scientific research. For example, Ban et al. applied the Segment Anything Model (SAM) to the identification of microstructural features in polycrystalline or multiphase microscopic images (Li et al., 2025). Zhao et al. explored the application of SAM in medical image segmentation, focusing on polyp identification under weakly supervised settings (Zhao et al., 2025). Bai et al. investigated the use of SAM for soil pore identification, extending its application to the analysis of complex porous media images (Bai et al., 2025).

Although conclusions drawn from cold-flow experiments conducted in a quasi-two-dimensional fluidized bed using DIA should be applied with caution when extrapolated to high-temperature reduction conditions, a systematic understanding of the intrinsic bed flow structures during the fluidization of high-density particles such as iron ore powders can still provide an important physical basis for subsequent, more refined experimental investigations and CFD–DEM numerical simulations. Quantitative characterization of such intrinsic mechanisms is therefore of practical significance for promoting the optimization and efficient operation of hydrogen-based fluidized bed metallurgical processes. Given that accurate segmentation of gas–solid flow structures is a key prerequisite for achieving these objectives, and that traditional threshold-based segmentation methods have shown clear limitations, while existing deep learning-based studies have generally lacked explicit identification of solid-phase structures—thereby constraining a comprehensive understanding of gas–solid two-phase flow mechanisms—the applicability of general-purpose visual segmentation models

to gas–solid flow analysis also remains to be systematically evaluated. Against this background, the present study aims to explore reliable segmentation strategies for gas–solid fluidization images and, based on the proposed approach, to analyze the fluidization behavior of high-density particles under different fluidization conditions.

2. Experimental

The schematic diagram of the miniature quasi-two-dimensional fluidized bed used in this study is shown in Fig. 1. The bed chamber of the two-dimensional bed is made of transparent plexiglass to allow a clear observation of the bubble and particle movement within the fluidized bed. The dimensions of the bed chamber are 100 mm in length, 5 mm in thickness, and 200 mm in height. The upper and lower air chambers of the bed are constructed from aluminum alloy. The air chambers and the bed chamber are secured together with screws, and silicone gaskets are placed between them to ensure the sealing of the entire apparatus. Between the lower air chamber and the bed chamber, two layers of 0.1 mm thick, 1200-mesh screens serve as the gas distributor.

Two pressure sensors are installed above the gas distributor and at the gas outlet, respectively, to monitor pressure fluctuations in the bed during the fluidization process. The gas flow control system includes two mass flow meters (Aurasky Electronics, China) with flow ranges of 50 L/min and 2 L/min, respectively. Both the pressure controller and the mass flow meters are computer-controlled, and software is used to record real-time data fluctuations. The fluidizing gases used in the experiments were hydrogen and nitrogen. Nitrogen, with a purity of 99.9%, was supplied by Haipu Gas Company (China), while hydrogen was supplied by a hydrogen generator providing a stable hydrogen supply.

The imaging system consists of a high-speed camera (Phantom, USA) and a fixed light source. The high-speed camera was used to capture images of the bubbles in the high-speed fluidization process, and the fixed light source was placed behind the miniature quasi-two-dimensional fluidized bed to enhance the contrast between the bubble phase and the solid phase. Each image capture was performed after the particles reached a stable fluidization state for 1 min to ensure that stable fluidization data were obtained. The high-speed camera was set to a frame rate of 200 fps, and the captured images had a resolution of 800×786 pixels, with each recording lasting for 1 min. To eliminate any randomness in the experimental results, each operating condition was recorded three times.

The particles used in the experiment were Iron Ore Powder (IOP),

Black Corundum (BC), and a mixed particle (MIX), with the mixed particle consisting of IOP and pure iron powder mixed in a 1:1 vol ratio. The three types of particles were first sieved using screens with an aperture size of 100–200 μm , and then analyzed for particle size distribution using a laser particle size analyzer (Malvern Panalytical, Model: Mastersizer, 2000). The particle size distribution results for the three particles are shown in the Supplementary Fig. S1. The minimum fluidization velocity of different particles was measured using the pressure drop method, as shown in Fig. S2, with the pressure data representing the downflow pressure. The average particle size, particle density, and corresponding minimum fluidization velocity are listed in Table 1.

During the experiment, pure N_2 was first used as the fluidizing gas to fluidize three different particles with similar diameters under gradually increasing fluidization numbers (F_n , defined as the ratio of the actual fluidization velocity to the minimum fluidization velocity of the particles). This set of experiments was conducted to investigate the effects of particle type and F_n on the fluidization behavior. Subsequently, IOP samples were used to explore the influence of hydrogen concentration in the fluidizing gas. Hydrogen was mixed into the nitrogen-based fluidizing gas at volume fractions of 10%, 20%, 30%, 40%, and 50%. The detailed experimental parameters are listed in Table 2.

3. Image segmentation methods

3.1. DeepLabV3+ framework

The DeepLab network was proposed by Chen and the Google research team for image segmentation tasks (Chen, Papandreou, et al., 2018; Chen, Zhu, et al., 2018). The architecture has undergone continuous development and was extended to the DeepLabV3+ version in 2018. The network adopts an encoder–decoder architecture, which efficiently integrates high-resolution image details with deep semantic information, thereby achieving superior image segmentation performance.

Table 1
Physical properties of particles used in the experiment.

Particle type	D_{50} (μm)	Bulk density (kg/m^3)	True density (kg/m^3)	Min. fluidization velocity (m/s)
IOP	161	2277.35	4163.16	0.0775
BC	198	1761.23	3102.68	0.0718
MIX	143	2476.21	4482.84	0.0789

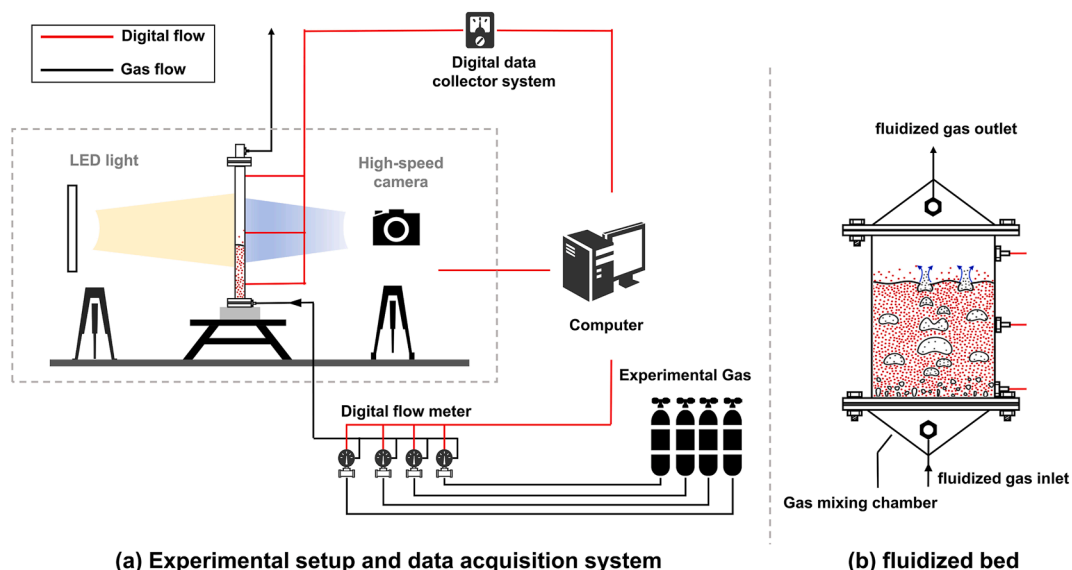


Fig. 1. Schematic of the miniature quasi-two-dimensional fluidized bed.

Table 2
Experimental parameters and operating conditions.

Experimental conditions	Experiment I (Section 4.2.1)	Experiment II (Section 4.2.2)
Particle type	IOP, MIX, BC	IOP
Initial bed height (mm)	60 mm	
Fluidization number	1.5 2.0 2.5 3.0	1.5
Type of fluidizing gas	Pure N ₂	N ₂ +H ₂
H ₂ fraction in fluidizing gas (vol%)	-	10, 20, 30, 40, 50

During model training, the encoder component is primarily responsible for feature extraction. The input images are first processed by a backbone network, which serves as the feature extractor and is designed to capture semantic information at different hierarchical levels. In general, the backbone is constructed using a deep convolutional neural network, accounting for the majority of the model parameters and constituting the main source of computational cost. Consequently, the choice of backbone network largely determines both the computational complexity and the segmentation performance of the model. In existing semantic segmentation studies, the ResNet family of networks (He et al., 2016, pp. 770–778) has been widely adopted as backbone architectures due to their favorable performance and training stability. By introducing residual connections, ResNet effectively alleviates the vanishing and exploding gradient problems commonly encountered in the training of deep neural networks, thereby enabling the optimization of much deeper architectures. Depending on network depth, the ResNet family includes ResNet-18, ResNet-34, and several deeper variants. In general, increasing network depth enhances feature representation capability, but at the cost of significantly higher computational and memory requirements. However, increased computational complexity does not necessarily lead to continuous improvements in segmentation accuracy. In particular, for semantic segmentation tasks with limited training samples and relatively regular target structures, excessively deep networks may introduce redundant computation or even lead to overfitting. Based on these considerations, comparative evaluations of DeepLabV3+ with ResNet backbones of varying depths are performed to balance segmentation accuracy and computational efficiency, thereby identifying the most suitable backbone for fluidized-bed image segmentation in this study.

After feature extraction by the backbone network, two types of feature maps are generated. The first consists of shallow feature maps, which are directly forwarded to the decoder to preserve high-resolution spatial details. The second consists of deep feature maps obtained from the final convolutional layer of the backbone. These deep features are fed into the Atrous Spatial Pyramid Pooling (ASPP) module, where four atrous convolutions with different dilation rates, together with one pooling operation, are applied to generate five sets of feature maps with different receptive fields. Atrous convolution effectively enlarges the receptive field without a significant increase in the number of trainable parameters. The resulting feature maps are then concatenated and passed to the decoder. The decoder performs upsampling and feature fusion on the context-rich representations, ultimately restoring the feature maps to the same spatial resolution as the input image. Owing to this architectural design, DeepLabV3+ has demonstrated reliable segmentation performance across a wide range of application domains.

3.2. Model training and computational efficiency

The dataset used for model training constitutes the foundation of deep learning-based approaches, and the quality of the dataset directly affects the robustness and generalization capability of the trained model. When constructing an image dataset for fluidized-bed applications, it is therefore essential to comprehensively consider the diversity of operating conditions and imaging environments, and to place particular emphasis on the annotation of complex scenarios to ensure sufficient

generalization ability. A total of 1000 training samples were annotated in this study, all of which were derived from experimental images of the IOP sample during fluidization. Considering that the fluidization behavior becomes increasingly intense with increasing Fn , resulting in more complex flow structures and greater identification difficulty, the dataset was deliberately designed to cover multiple representative fluidization states. Specifically, four fluidization numbers ($Fn = 1.5, 2.0, 2.5$ and 3.0) were included, and the corresponding sample size followed a ratio of 1:2:3:4. The gas (bubble) phase and the solid phase in each image were manually annotated using the LabelMe (Russell et al., 2008) software. The resulting dataset was then divided into a training set and a validation set at a ratio of 85% to 15%. To enhance the diversity of the training data and improve the generalization performance of the model, data augmentation techniques were applied during training, including image flipping, rotation, and Gaussian blurring. These operations effectively increased the number of images participating in the training process and improved the robustness of the model to variations in image appearance.

In this study, the DeepLabV3+ model was trained based on the PyTorch deep learning framework. The training was conducted on a hardware platform equipped with two NVIDIA GeForce RTX 4090 GPUs, each with 24 GB of memory. To fully exploit the parallel computing capability of the GPUs, training samples were fed into the model in batches, with the batch size set to 8. The stochastic gradient descent (SGD) optimizer was employed for parameter updates, with an initial learning rate of 0.01. A polynomial learning rate decay strategy was adopted during training to dynamically adjust the learning rate, thereby improving convergence stability and reducing oscillations in the later stages of training. The cross-entropy loss function was used to evaluate segmentation performance. In addition, momentum and weight decay terms were incorporated into the optimization process to suppress overfitting and further enhance the model's generalization ability. Furthermore, a periodic validation scheme and an early stopping mechanism were introduced to improve training efficiency and prevent overfitting. Specifically, the validation loss was computed on the validation set every five epochs to continuously monitor the model's performance. The early stopping mechanism terminated the training process when no significant decrease in validation loss was observed over ten consecutive evaluations, and the model parameters corresponding to the best validation performance were retained. This training strategy ensured adequate generalization performance while avoiding unnecessary training iterations, thereby effectively reducing computational cost.

Segmenting the bubble phase and solid phase in a fluidized bed using a deep learning model is essentially a three-class classification problem (Class 1: background; Class 2: bubble phase; Class 3: solid phase). In image segmentation tasks, the confusion matrix is commonly employed to evaluate the classification performance of the model across different classes. The confusion matrix provides a quantitative description of correct classifications and misclassifications for each class. Taking the bubble phase as an example, the structure of the corresponding confusion matrix is shown in Table 3. In this context, TP (True Positive) denotes the pixels that actually belong to the bubble phase and are correctly predicted as bubble pixels; FP (False Positive) denotes the pixels that actually belong to the solid phase or background but are incorrectly predicted as bubble pixels; TN (True Negative) denotes the pixels that actually belong to the solid phase or background and are correctly predicted as non-bubble pixels; and FN (False Negative)

Table 3
Confusion matrix structure for bubble phase segmentation.

True label Predicted result	Bubble phase	Solid phase or background
Bubble phase	TP	FN
Solid phase or background	FP	TN

Table 4

Performance comparison of different backbone networks.

Backbone	ResNet18	ResNet34	ResNet50	ResNet101
Validation loss	0.03057	0.03248	0.03340	0.03164
Pixel accuracy	0.989	0.989	0.988	0.989
Mean IoU	0.948	0.949	0.946	0.945
Total parameters (M)	16.6	26.71	40.35	59.34
GPU memory (MiB)	8161	15069	18094	20845
Model size (MB)	127	213	323	475
Time per epoch (s)	10.17	12.53	18.62	23.72

denotes the pixels that actually belong to the bubble phase but are incorrectly predicted as solid or background pixels. Based on the values of TP, FP, TN, and FN extracted from the confusion matrix, key evaluation metrics such as Pixel Accuracy (PA) and Intersection over Union (IoU) can be further calculated.

Pixel Accuracy (PA) refers to the ratio of correctly predicted pixels to the total number of predicted pixels. In this study, it is defined as the proportion of correctly predicted bubble and solid phase pixels to the total number of pixels in the image. The formula is described as follows:

$$PA (ACC) = \frac{TP + TN}{TP + FP + FN + TN}$$

Intersection over Union (IoU) is a metric used to evaluate the performance of image segmentation, representing the overlap between the predicted and ground truth regions. Mean Intersection over Union (MIoU) is the average IoU across all classes, providing an overall measure of segmentation performance in multi-class tasks. The formula is described as follows. In this study, the number of classes C is 3, including the bubble phase, solid phase, and background.

$$IoU = \frac{TP}{TP + FP + FN}$$

$$MIoU = \frac{1}{C} \sum_{i=1}^C IoU_i$$

The training loss and PA of DeepLabV3+ models with ResNet backbones of different depths are illustrated in Fig. S3, and the corresponding final model accuracy metrics and computational resource consumption are summarized in Table 4.

The training code, selected dataset, and test images for the DeepLabV3+ model have been made publicly available for research and verification at: <https://github.com/Pensword0/BubbleSeg>.

3.3. Image analysis methods

Since the segmentation results produced by the deep learning model are inherently represented in pixel space and cannot be directly used for physical analysis, a pixel-to-physical mapping procedure was established to convert pixel-level information into quantitative physical parameters. Based on this mapping procedure, fluidization characteristics with clear physical meanings, including bubble size, bubble rising velocity, and bed expansion ratio, can be further extracted. Specifically, bubble size and rising velocity are used to characterize the intensity of gas–solid mixing, thereby providing a basis for selecting appropriate superficial gas velocities and avoiding excessive bubble coalescence or slugging. Meanwhile, macroscopic solid-phase parameters such as the bed expansion ratio serve as indicators of overall bed stability and solids holdup, which are relevant for identifying stable operating windows and assessing the load capacity of industrial fluidized-bed reactors. The definitions and calculation methods of these parameters are summarized as follows.

The areas of the bubble phase and the solid phase correspond to the total number of pixels occupied by each phase in the segmentation results. Taking the bubble phase as an example, the bubble area A_b is calculated as the sum of pixels classified as bubble phase:

$$A_b = \sum b(x_j, y_j)$$

Where $b(x_j, y_j)$ is an indicator function that equals 1 if the pixel at location (x_j, y_j) is classified as the bubble phase, and 0 otherwise.

Since the segmented bubble and solid regions generally exhibit irregular geometries, an equivalent diameter is introduced to characterize their representative size. The equivalent bubble diameter D_b is defined as:

$$D_b = \sqrt{\frac{4A_b}{\pi}}$$

The bubble velocity is defined as the displacement of the bubble centroid per unit time, including the horizontal velocity V_h and the vertical velocity V_v . By tracking the centroid of the same bubble in two consecutive frames and dividing the displacement by the time interval Δt , the bubble velocities are calculated as:

$$V_v = \frac{y_b(t + \Delta t) - y_b(t)}{\Delta t}$$

$$V_h = \frac{x_b(t + \Delta t) - x_b(t)}{\Delta t}$$

Where $(x_b(t), y_b(t))$ and $(x_b(t + \Delta t), y_b(t + \Delta t))$ denote the centroid coordinates of the same bubble at times t and $t + \Delta t$, respectively.

Benefiting from the simultaneous discrimination between the gas phase and the solid phase, the present study is able not only to accurately identify bubble structures, but also to analyze several fluidization characteristics based on the solid-phase region.

To characterize the volumetric proportion of the bubble phase within the solid-gas system, the bubble volume fraction (denoted as ϕ_b) is introduced and defined as the ratio of the bubble-phase volume V_b to the total volume of the bubble phase and the solid phase:

$$\phi_b = \frac{V_b}{V_b + V_s}$$

It should be noted that, since a large amount of gas remains within the emulsion phase of a fluidized bed without forming distinct bubble structures, the bubble volume fraction defined here reflects only the proportion of the identifiable bubble phase within the bed. Consequently, its value is generally lower than the conventional bed voidage ϵ defined in classical fluidization theory based on the total gas phase. Nevertheless, this parameter still provides useful reference information for understanding the fluidization behavior.

In fluidized-bed experiments, the fluctuation scale of the bed surface is typically difficult to quantify. Owing to the accurate segmentation of the solid-phase region achieved in this study, the spatiotemporal evolution of the free bed surface can be clearly identified, enabling precise determination of the bed height.

Based on the bed surface position determined from the boundary of the solid-phase region, the instantaneous bed height $H(t)$ can be obtained, allowing further analysis of the dynamic bed expansion behavior during fluidization.

To characterize the macroscopic expansion of the bed under stable fluidization conditions, the bed expansion ratio e is introduced and defined as the relative change in the average bed height H after fluidization with respect to the initial fixed-bed height H_0 :

$$e = \frac{H - H_0}{H_0}$$

Before conducting quantitative scientific analyses based on image-processing techniques, one critical step that has rarely been discussed in detail in previous studies is the calibration between pixel scale and real physical length. In practice, this step can constitute a significant source of error, particularly when an inappropriate reference scale is

selected for calibration. Specifically, calibration should preferentially be performed using a reference length that is sufficiently large in physical scale.

In the present study, when the thickness of the acrylic plate (2 mm) was used as the calibration reference, the measured pixel length varied between 11 and 14 pixels due to image resolution limitations and unavoidable interpretation uncertainty. This resulted in an estimated spatial resolution ranging from 5.5 to 7 pixel mm^{-1} , corresponding to a relative error of approximately 20%. By contrast, when the bed width (100 mm) was used as the calibration reference, the measured pixel length varied only from 570 to 575 pixels, yielding spatial resolutions of 5.70–5.75 pixel mm^{-1} and a relative error of less than 1%. These results demonstrate that using a larger reference length for spatial calibration can substantially reduce the impact of pixel quantization error on the final quantitative results. Given that this issue is of general relevance to image-based quantitative analyses, it is explicitly highlighted here.

4. Results

4.1. Segmentation results

Given that accurate segmentation of flow structures is crucial for the quantitative analysis of fluidization behavior, this study compares the applicability of different image segmentation methods for identifying flow structures in a bubbling fluidized bed. Specifically, the widely used Otsu adaptive thresholding method, the latest version of the general-purpose segmentation foundation model SAM3, and a DeepLabV3+ model trained on the experimental dataset in this study were selected for comparative analysis of their segmentation performance.

Adaptive thresholding is a classical image segmentation approach based on the statistical characteristics of the gray-level histogram. Among these methods, the Otsu algorithm automatically determines a global optimal threshold by maximizing the between-class variance

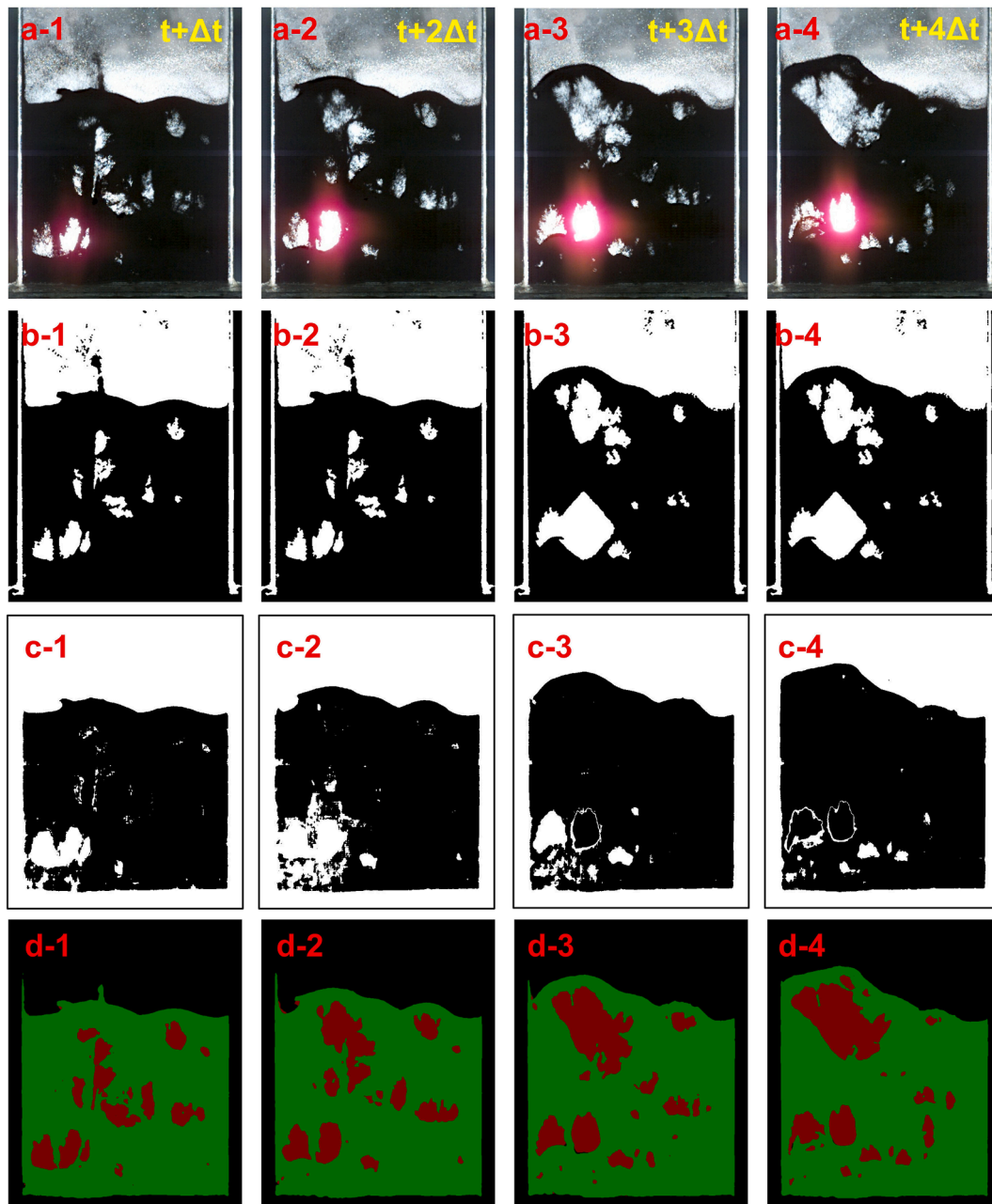


Fig. 2. Segmentation results of flow structures over consecutive time frames. (a) Original images; (b) Otsu adaptive thresholding; (c) SAM3; (d) DeepLabV3+.

between the foreground and background, thereby achieving foreground–background separation. The SAM3 is a recently proposed general-purpose image segmentation foundation model, which acquires the capability to segment multiple object categories and complex scenes through large-scale training, and can perform image segmentation without task-specific retraining. For the DeepLabV3+ model trained in this study, the inference output separates the gas phase (shown in red) and the solid phase (shown in green), while the black regions correspond to background areas unrelated to the experiment.

Fig. 2 presents a comparison of the segmentation results obtained by three different methods for the IOP sample at $Fn = 2$, based on four consecutive frames captured over a short time interval, where the shown images were not included in the training dataset of the deep learning model. As shown in the figure, the conventional Otsu adaptive thresholding method (Fig. 2(b)) can effectively segment relatively large bubbles when the image exhibits clear intensity contrast (e.g., Figs. 2(b-1)).

However, in the presence of local overexposure, its segmentation performance deteriorates significantly and is easily affected by background objects with gray levels similar to that of the bed, leading to noticeable false detections, such as those observed near the top of the image. By contrast, SAM3 (Fig. 2(c)) is mainly capable of identifying the overall contour of the bed, but shows limited ability in segmenting bubble structures within the bed, making it difficult to accurately capture bubble morphology. In comparison, the DeepLabV3+ model exhibits more stable segmentation performance under varying imaging conditions. It not only enables effective segmentation of bubbles within the bed even when image quality is degraded, but also accurately distinguishes solid-phase regions in complex backgrounds, thereby providing a reliable basis for subsequent quantitative analysis of bed voidage and bed fluctuation characteristics.

Fig. 3 presents fluidization images obtained under different Fn to evaluate the applicability and stability of different image segmentation

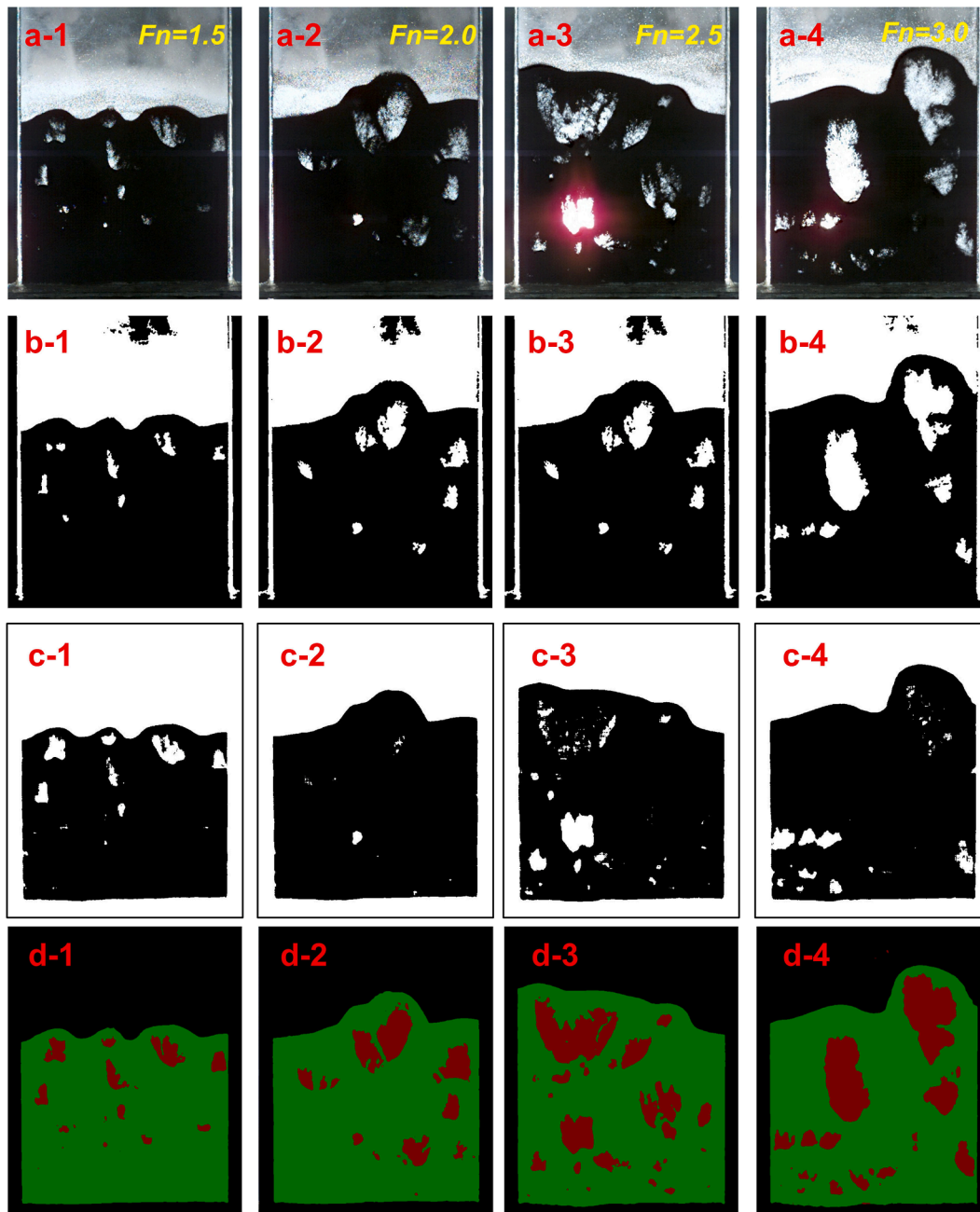


Fig. 3. Segmentation results of flow structures under different Fn . (a) Original images; (b) Otsu adaptive thresholding; (c) SAM3; (d) DeepLabV3+.

methods under varying fluidization states, where the images shown were not included in the training dataset of the deep learning model. As shown in the figure, the Otsu adaptive thresholding method is strongly influenced by dark background objects, causing some background regions to be misidentified as part of the bed. In addition, this method shows limited capability in segmenting small-scale bubbles and often fails to capture fine bubble structures within the bed; however, it performs relatively well in identifying isolated large bubbles with clear gray-level contrast. The segmentation results of SAM3 exhibit pronounced instability: although the fluidization structures can be reasonably identified at $Fn = 1.5$, the segmentation performance deteriorates markedly as Fn increases and the internal bed dynamics become more intense. In contrast, the DeepLabV3+ model maintains relatively consistent segmentation performance across different fluidization states, thereby providing more stable identification of bed structures and bubble morphologies.

Overall, conventional threshold-based segmentation methods still exhibit pronounced limitations in bubble identification within fluidized beds, and struggle to stably resolve internal flow structures under complex imaging conditions. As a general-purpose segmentation model designed for large-scale scenes, SAM3 shows limited competitiveness when applied without task-specific training, and its segmentation performance remains inferior to that of specialized models trained for particular application scenarios. By contrast, after jointly incorporating both gas-phase and solid-phase regions as segmentation targets in this study, the DeepLabV3+–based model enables further analysis of macroscopic characteristics such as bed fluctuations and voidage at the global scale. Moreover, at the local scale, it is capable of identifying bubble eruption and particle entrainment processes at the bed surface, thereby providing new opportunities for a more refined characterization of fluidization behavior.

Although the DeepLabV3+ model demonstrates significantly superior segmentation performance compared with conventional threshold-based methods and the recently proposed general-purpose segmentation model SAM3, its inference results still inevitably contain a small number of noisy pixels and misclassified regions. These misidentifications are mainly concentrated in two aspects: (i) background regions that exhibit gray-level or texture characteristics highly similar to those of the bed, and (ii) particle entrainment regions near the bed surface induced by bubble eruption under high Fn . To address these issues, a customized post-processing procedure was developed to remove and correct the evidently misclassified noise pixels and bed-surface regions in the images produced by the deep learning model, and to crop redundant background areas, thereby facilitating subsequent statistical and quantitative analyses. The complete workflow of the gas–solid two-phase segmentation and the corresponding post-processing results are illustrated in Fig. 4.

4.2. Statistical characteristics of bubbles based on image segmentation

4.2.1. Fluidization states of different particles at various Fn

Since the images captured by the high-speed camera contain a large number of bubbles, it is impractical to analyze the flow characteristics of each bubble individually. Therefore, to reflect the statistical patterns of bubbles throughout the flow process, the bed height was divided into intervals of 5 mm. Bubbles with centroids falling within each interval were analyzed statistically, as illustrated in Fig. S4.

Fig. 5 shows the variation of bubble size with bed height for three different types of particles. Each data point in the figure reflects the statistical pattern of a large number of bubbles within a specific interval. From the data, it can be observed that, under all conditions, bubble size increases with bed height, indicating that bubbles grow as they rise. At relatively low Fn , at the same bed height, bubbles in the IOP sample are the smallest, whereas bubbles in the MIX sample are the largest. As the Fn increases, stronger bed fluctuations make it difficult to clearly distinguish a consistent trend. However, as bubbles continue to develop and approach the gas–solid interface, intense bubble coalescence and fragmentation occur, making it challenging to assess further bubble development. As a result, data from this region lack statistical significance in the analysis.

Figs. 6 and 7 respectively show the probability density of bubble area and bubble aspect ratio for three different particles under four progressively increasing Fn . From the figures, it can be observed that, as the Fn increases, the bubble size for all three particle systems increases correspondingly. Notably, at a low fluidization number ($Fn = 1.5$), the probability density curves of bubble area for the IOP sample exhibit relatively high and narrow peaks, indicating a highly concentrated bubble size distribution with low variability and high consistency. In addition, at relatively low fluidization numbers ($Fn = 1.5$ and 2.0), the bubbles in the BC sample are the largest, whereas those in the IOP sample are the smallest, with pronounced differences in bubble size among the three particle systems. This suggests that the bubble population in the IOP system is characterized by a large number of small bubbles. With further increases in the Fn , the bubble area in the MIX system shows the most pronounced growth. When the fluidization number increases to $Fn = 3.0$, the bubble areas in the three particle systems become nearly identical. Therefore, compared to the other two samples, the fluidization of IOP is more uniform and stable. Based on the relevant data analysis from Fig. 7, the bubble aspect ratio does not show a significant correlation with either the Fn or the particle type during the fluidization process. However, overall, the bubble aspect ratio is greater than 1 under all conditions, indicating that the bubbles exhibit an elongated shape in the direction of gas flow, which is intuitively reasonable. To better visualize this vertically stretched bubble morphology and the corresponding bed structure evolution, Fig. S5 presents representative segmented images of the IOP sample at different fluidization numbers.

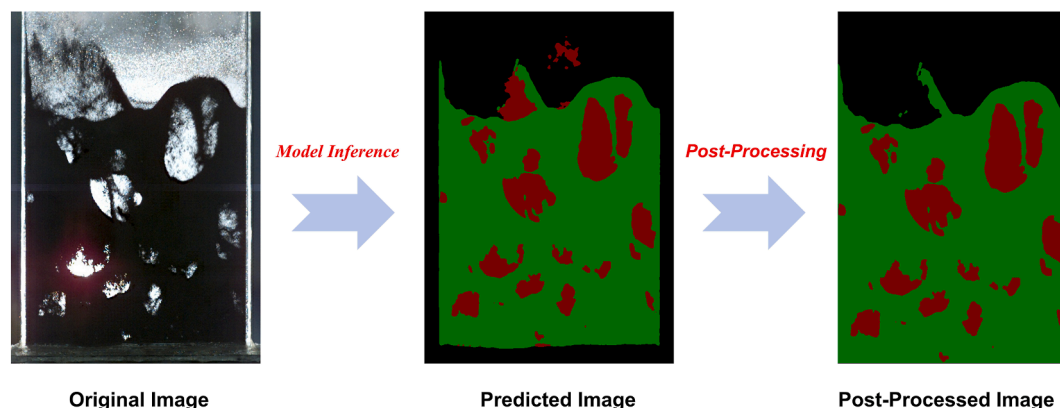


Fig. 4. Deep learning-based gas–solid segmentation flowchart.

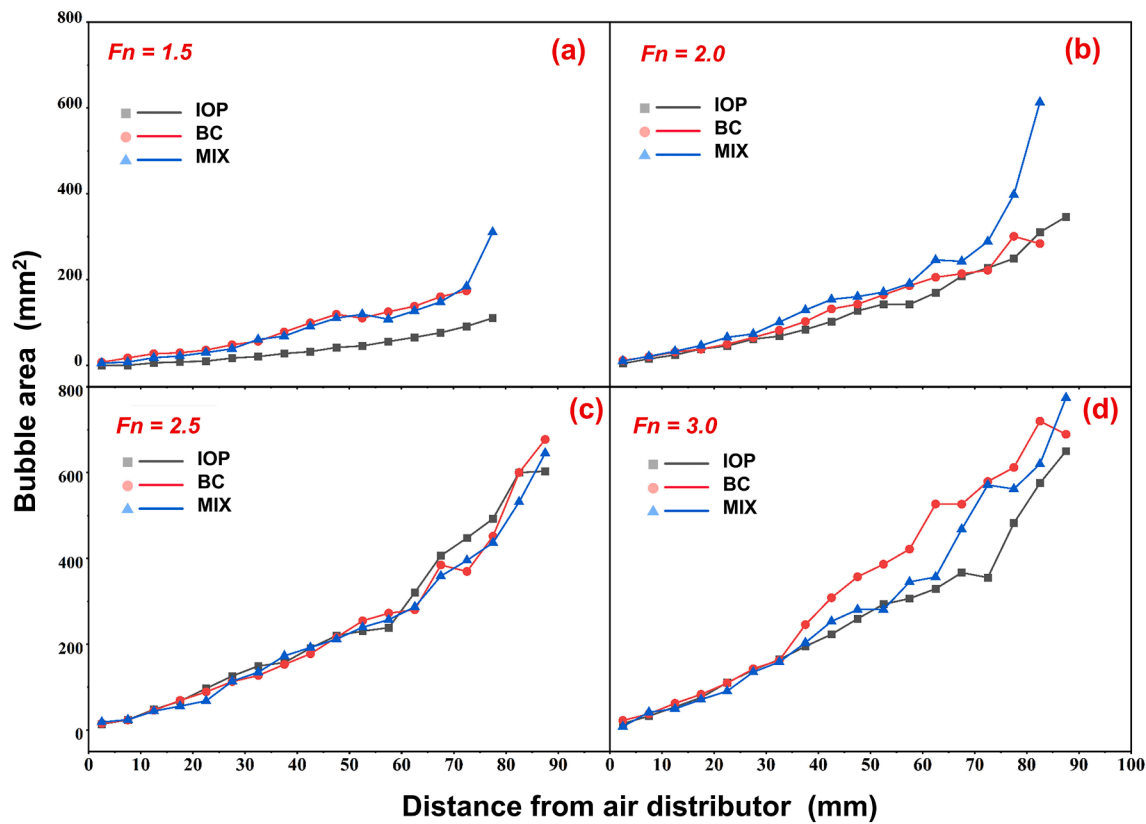


Fig. 5. Variation of bubble size with bed height.

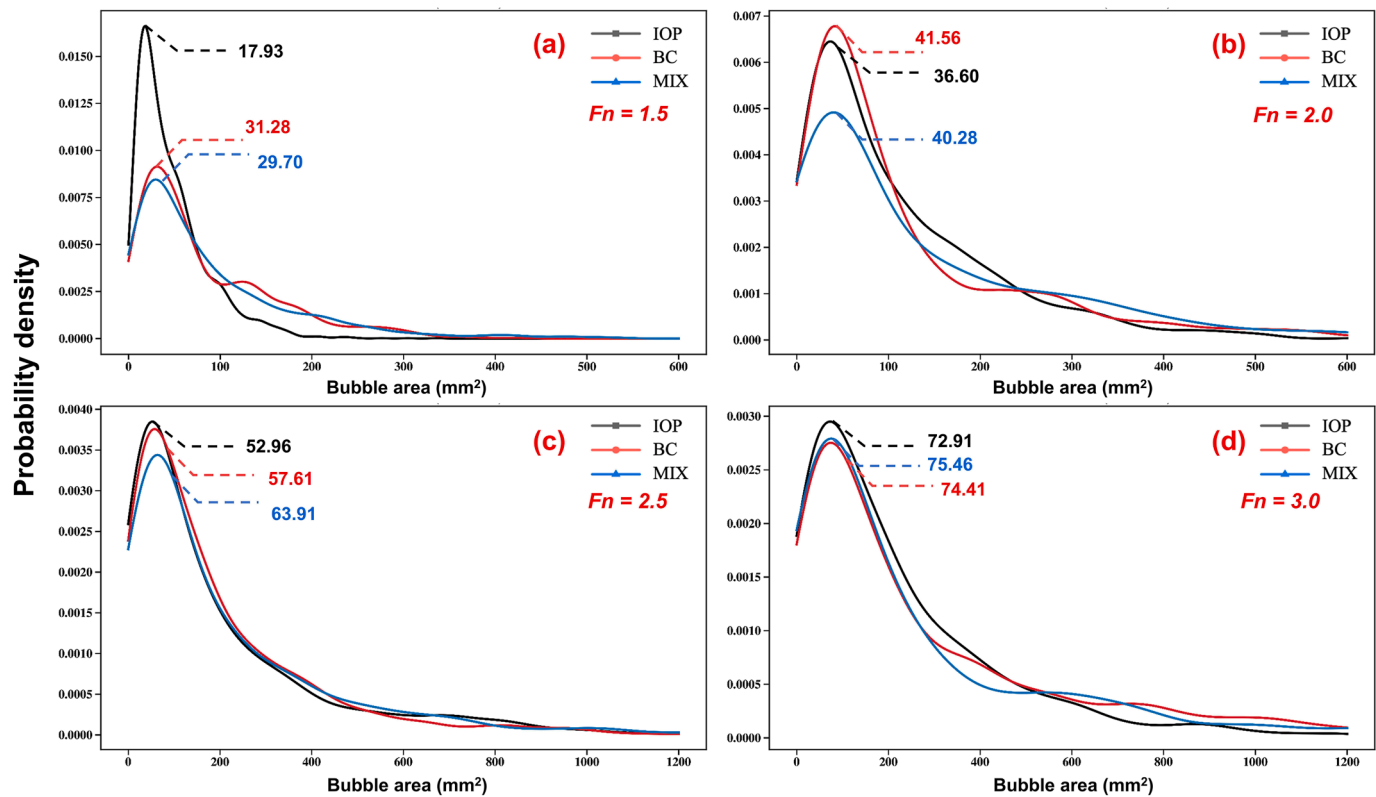


Fig. 6. Probability density of bubble area.

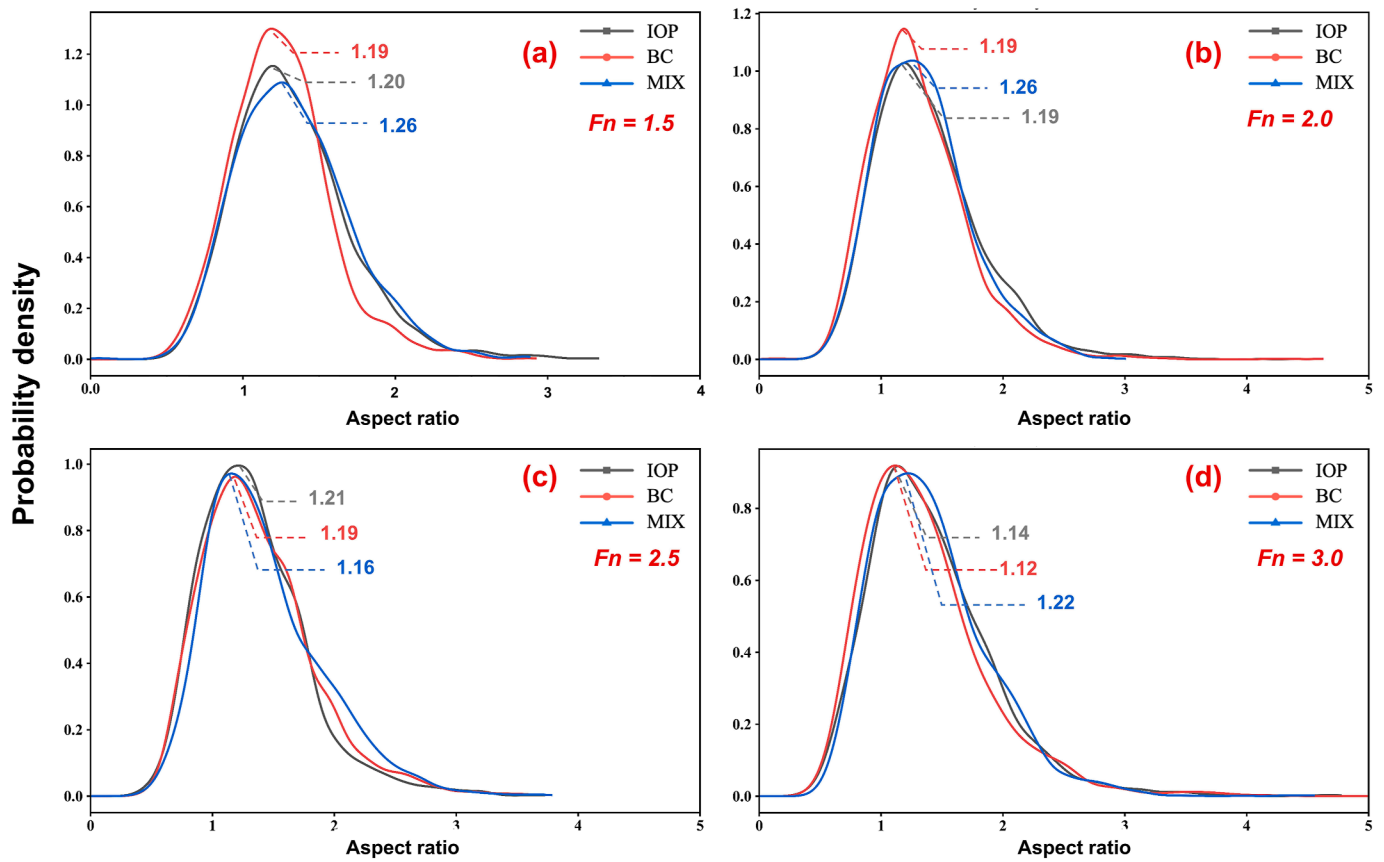


Fig. 7. Probability density of bubble aspect ratio.

Fig. 8 shows the relationship between bubble rising velocity and bubble size for three different particles under four fluidization numbers. A clear positive correlation is observed, with larger bubbles exhibiting higher rising velocities. Significant differences in bubble rising velocity

are also evident among the three particle systems: bubbles in the IOP sample rise most slowly, whereas those in the MIX sample rise the fastest. This suggests that gas–solid interactions in the IOP system are more uniform, resulting in a comparatively more stable fluidization state.

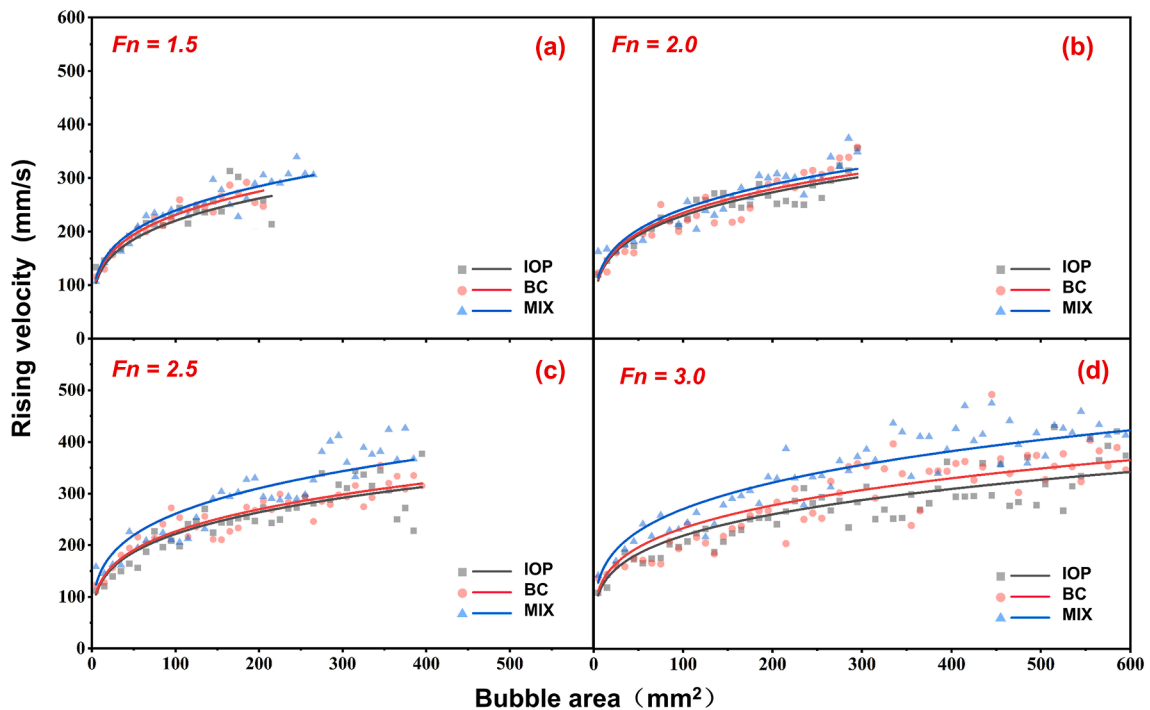


Fig. 8. Relationship between bubble rising velocity and bubble size.

4.2.2. Fluidization state of IOP under hydrogen-rich atmosphere

Fig. 9 illustrates the relationship between bubble size and vertical height under five hydrogen-containing atmospheres. It can be observed that, compared to a pure nitrogen atmosphere, bubbles are significantly smaller at the same height when hydrogen is present. Furthermore, the bubble size generally decreases with increasing hydrogen concentration. However, it should be noted that the suppressing effect of hydrogen concentration on bubble size exhibits a noticeable marginal effect, with the reduction trend becoming progressively weaker as the hydrogen concentration continues to increase.

A statistical analysis of bubble size was conducted based on images captured under six different atmospheres, and the results are presented in the form of probability density distributions. Fig. 10 shows the probability density of bubble area under different hydrogen concentrations. It can be observed that the introduction of hydrogen into the fluidizing gas reduces bubble size during fluidization. However, with further increases in hydrogen concentration, the extent of bubble size reduction becomes noticeably weaker. Fig. 11 presents the probability density of bubble aspect ratio under different hydrogen concentrations. It is evident that the bubble aspect ratio remains around 1.20 under all six different atmospheres, indicating that the bubbles maintain an elongated shape throughout the fluidization process, with minimal influence from the hydrogen concentration in the fluidizing gas.

Fig. 12 shows the relationship between bubble size and bubble rising velocity under six different atmospheres. As observed from the figure, the rising velocity of bubbles with the same size does not exhibit

significant variation across different hydrogen concentrations in the fluidizing gas, showing only a slight decrease within a narrow range and no clear trend. This indicates that during particle fluidization, the rising velocity of bubbles is primarily determined by their size, with little correlation to other factors.

For fluidized systems, variations in the bed structure itself also constitute an important issue that warrants attention. Fig. 13 illustrates the variations in bubble volume fraction and bed expansion ratio with increasing hydrogen concentration. It can be observed that both the bubble volume fraction and the bed expansion ratio gradually decrease as the hydrogen concentration increases. Compared with a 100%N₂ atmosphere, a pronounced reduction in bubble volume fraction is observed when the H₂ concentration reaches 50%, indicating that the bubble characteristics within the bed differ significantly from those under pure N₂ conditions. To visually demonstrate this change, Fig. S6 presents representative raw images of the fluidization process along with their corresponding segmentation results. The variation in bubble volume fraction is more pronounced when hydrogen is initially introduced into the fluidizing gas; however, as the hydrogen concentration continues to increase, further hydrogen addition has a limited effect on the bubble volume fraction. In principle, bed expansion is expected to exhibit a high degree of consistency with the variation in bubble volume fraction. Although the overall trends are generally consistent, minor discrepancies can still be observed. These discrepancies may be associated with the fact that a portion of the gas does not form identifiable bubble structures but instead enters the emulsion phase. Under such

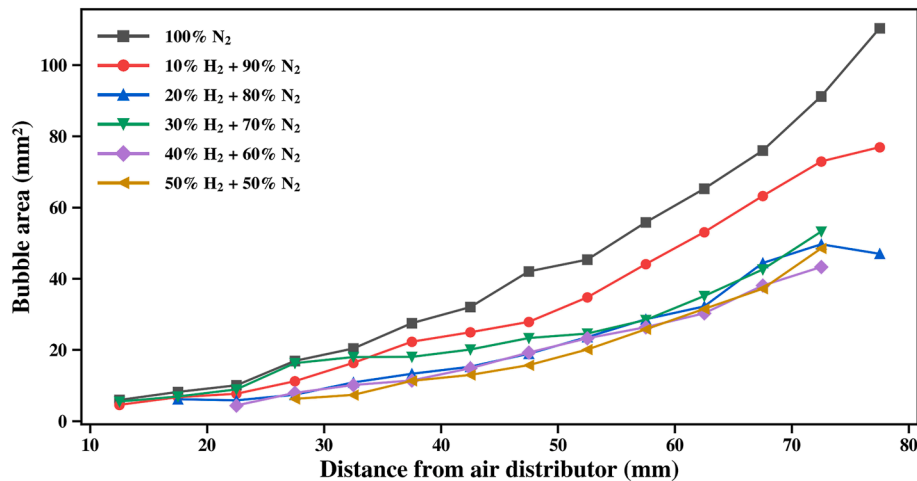


Fig. 9. Variation of bubble size with bed height.

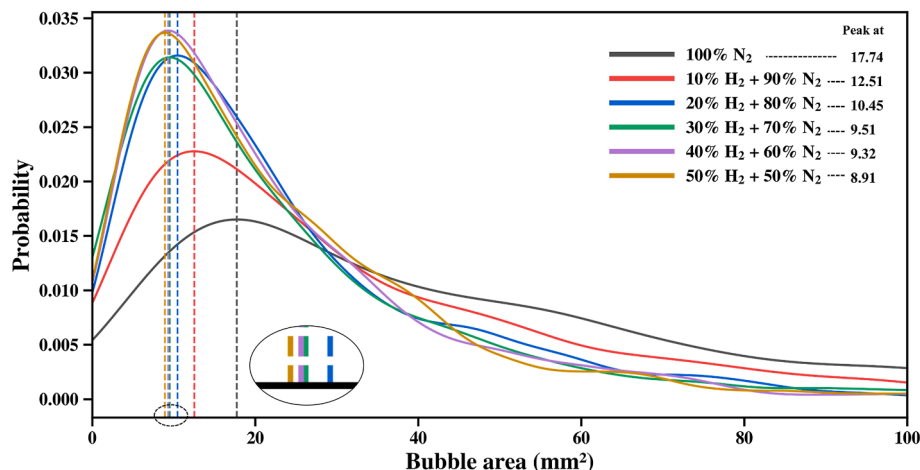


Fig. 10. Probability density of bubble area.

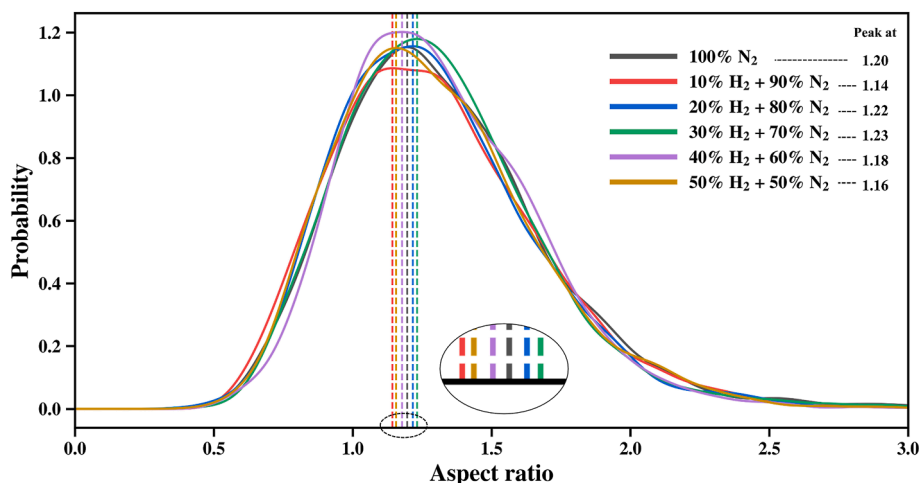


Fig. 11. Probability density of bubble aspect ratio.

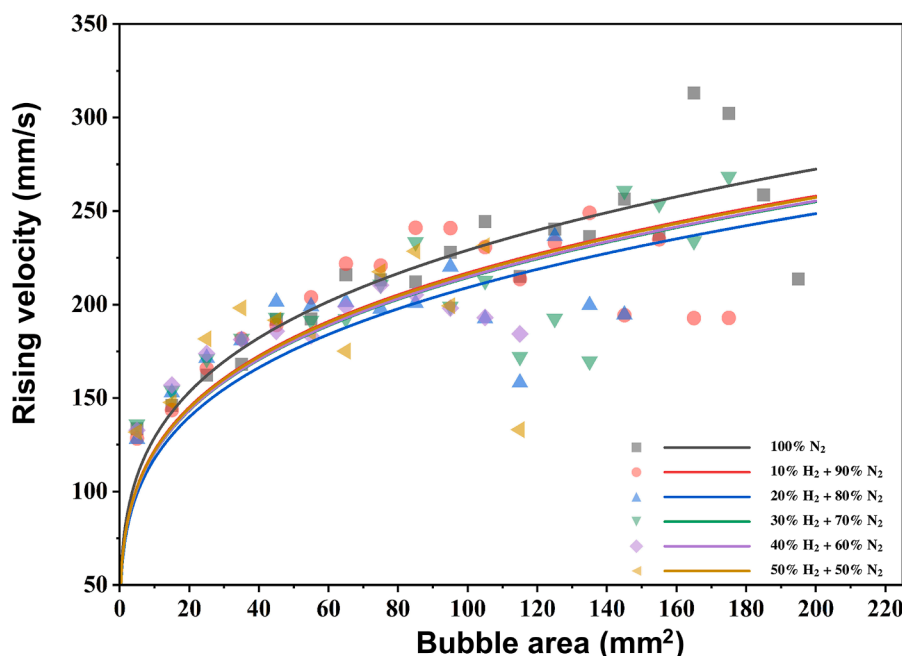


Fig. 12. Relationship between bubble rising velocity and bubble size.

conditions, the gas is mainly distributed in a dispersed manner within the interparticle voids. Given that the present study focuses on the statistical characteristics of identifiable bubble structures, the gas partitioning between the emulsion phase and the bubble phase is not further elaborated here and may be systematically evaluated in future studies using more refined experimental techniques or numerical simulations.

5. Conclusions

In this study, fluidization images inside a quasi-two-dimensional fluidized bed were captured using a high-speed camera, and a deep learning-based DeepLabV3+ framework was employed to achieve simultaneous segmentation of the gas and solid phases. Meanwhile, the proposed method was compared with conventional threshold-based segmentation methods and the general-purpose foundation model SAM3 in terms of recognition performance. Based on the developed segmentation approach, representative effects of different fluidization numbers and fluidizing gas atmospheres on key fluidization parameters were analyzed to demonstrate the capability of the method for

quantitative characterization of gas–solid hydrodynamics. It should be emphasized that this study serves as a methodological validation of a machine-learning-assisted digital image analysis framework under well-controlled and visually accessible fluidization conditions typically encountered in laboratory-scale studies. The approach provides a transferable workflow for quantitatively extracting bubble-scale hydrodynamic information and can be applied to cold-flow experiments, data-driven analysis, and validation of CFD–DEM or reduced-order models. Extension to more complex environments, such as high-temperature processes and chemically reacting flows, will require task-specific retraining and careful consideration of material evolution and imaging constraints, which constitute important directions for future work. The main conclusions of this study are summarized as follows:

- (1) The results indicate that the backbone network dominates the parameter scale of the model and has a significant influence on both training cost and segmentation performance. Comparative studies of different backbone networks show that using ResNet18

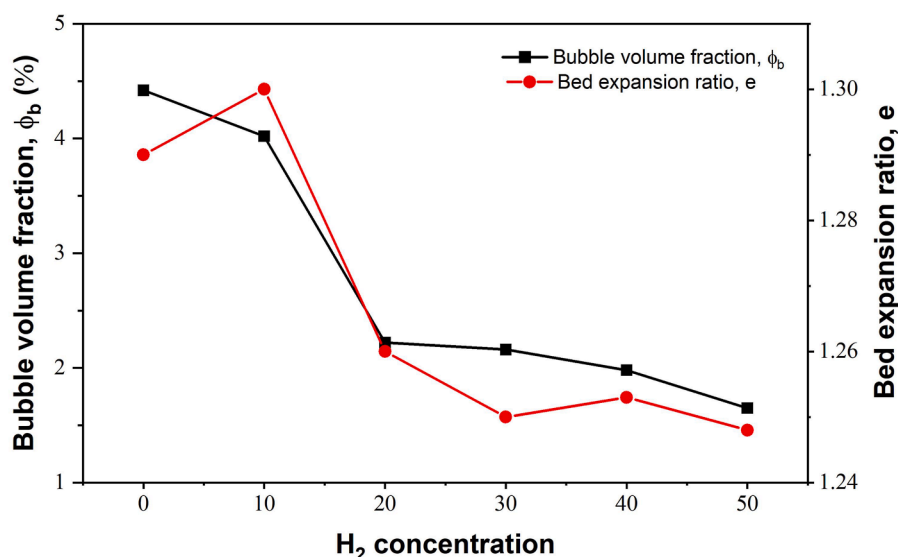


Fig. 13. Variation of ϕ_b and e with H_2 concentration.

as the backbone achieves the optimal overall performance, maintaining high segmentation accuracy while significantly reducing computational cost compared with other ResNet architectures. The training code has been made publicly available on GitHub (link omitted).

- (2) Compared with conventional segmentation methods and the general-purpose foundation model SAM3, the DeepLabV3+ framework demonstrates clear advantages in fluidization image segmentation. The proposed method maintains stable and accurate segmentation performance under different background and lighting conditions. Traditional threshold-based methods perform poorly for small bubbles and complex backgrounds, whereas SAM3, without task-specific training on fluidized bed images, can only roughly identify the solid-phase contours and shows limited capability in resolving bubble structures within the bed.
- (3) Under a pure N_2 atmosphere, IOP particles exhibit a more uniform and stable fluidization behavior. At the same fluidization number, the IOP particle system generates smaller bubbles with lower rising velocities, indicating that bubbles formed during IOP fluidization are characterized by smaller sizes, higher number density, and slower rise. With the addition of H_2 to the fluidizing gas, the bubble size decreases further and the bed expansion ratio is reduced, while the variations in bubble shape and rising velocity remain insignificant.

CRedit authorship contribution statement

Chuanhao Wang: Writing – original draft, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Yuchen Liu:** Writing – review & editing, Validation. **Jiehan Zhang:** Writing – review & editing, Methodology. **Shiyuan Li:** Resources, Project administration, Methodology, Funding acquisition.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.partic.2026.03.014>.

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