

Comparative study of deep learning techniques for predicting bubble dynamics in a gas-solid fluidized bed

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ABSTRACT

The dynamic characteristics of bubbles are pivotal for the design and optimization of gas-solid fluidized beds. Common techniques for bubble analysis include direct photography, Electrical Capacitance Tomography (ECT), and X-ray imaging, among others. Traditional image segmentation methods often struggle to accurately process a substantial number of digital images within complex background environments. This paper presents a deep learning-based semantic segmentation methodology specifically designed for bubble segmentation in gas/iron ore powder fluidized beds and assesses the segmentation performance of five distinct deep learning models. Based on training outcomes, the DeepLabV3+ model utilizing a ResNet50 backbone demonstrates superior performance. Building upon this optimal deep learning model, various kinetic characteristics of bubbles, including equivalent diameter, size distribution, aspect ratio, bed voidage, and rising velocity, are analyzed at different fluidization numbers ($n = 1.5, 2, 2.5, 3$) within a quasi-2D fluidized bed setup. The findings indicate that the fluidization number significantly affects the evolution of bubble size and equivalent diameter in the fluidized bed; notably, the average equivalent diameter tends to increase with height along the bed. Conversely, the influence of fluidization number on both bubble size distribution and aspect ratio distribution is relatively minor. As both fluidization number and height from the sieve plate increase, bed voidage rises while fluctuations intensify considerably. Furthermore, bubble rising velocity correlates positively with increasing equivalent diameter; however, it remains independent of fluidization number for bubbles of identical sizes.

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1. Introduction

Fluidization refers to a physical phenomenon where solid particles, when acted upon by rising gas or liquid with viscous drag, exhibit a suspended state resembling fluid-like properties. With different gas velocities, fluidization undergoes a transition from particulate fluidization to aggregated fluidization. Particulate fluidization typically exists only in theory, as complex forces between particles often result in uneven force distribution among particles, leading to irregular movements and the transition from particulate fluidization to aggregated fluidization.

Due to its high efficiency in heat and mass transfer, as well as good bed stability, gas-solid fluidized beds have been widely used

in industrial fields such as chemical engineering, combustion, and separation (Fu et al., 2019; Singh et al., 2020; Zhang et al., 2020). As the particulate fluidization state is unstable and easily transitions to aggregated fluidization, the latter has become the primary mixing mode in gas-solid fluidized beds. In this process, gas plays a crucial role in mass and heat transfer (Feng et al., 2021; Laihong et al., 2019; Yue et al., 2021). The intense circulation and agitation of solid particles and gas during continuous flow in the interior of gas-solid fluidized beds result in a considerable distribution of residence time for both the gas and solid phases. Prolonged residence time leads to highly uneven distribution of reactants within the fluidized bed. As air passes through the bed in the form of bubble, the contact opportunity between the gas and solid phases is reduced, resulting in insufficient reaction of the reactants and reduced heat transfer efficiency (Jie et al., 2017; Keshavarzi et al., 2014; Yunlong et al., 2011).

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The accurate segmentation of bubble is fundamental for studying bubble motion behavior. Currently, techniques for measuring bubble size and distribution include direct photography, X-ray imaging (Maurer et al., 2015), nuclear magnetic resonance (NMR) (Gladden et al., 2005), and digital image analysis (DIA) (Busciglio et al., 2008).

Once digital images are obtained, they need to be segmented. Traditional image segmentation methods mainly include the simplest pixel thresholding and pixel clustering (Cheng & Fu, 2020, pp. 6750–6753). In the context of gas-solid fluidized bed bubble segmentation, the common approach is to convert the acquired high-speed images directly into grayscale images, or to binarize the images based on thresholds. Both methods are highly dependent on the clarity of the images, as well as local spatial features such as boundary pixel characteristics. Furthermore, most images obtained under various conditions suffer from issues such as overlapping, out-of-focus images and uneven lighting, making bubble features difficult to segment. If fixed thresholding is used for image segmentation, the variability and unclear boundaries of bubbles can lead to detail being obscured by overly strong image lines. The distribution patterns of weaker edges may be covered, making it difficult to accurately extract bubble contours.

In recent years, rapid advancements in computer hardware, represented by GPUs, and the maturation of deep learning algorithms have occurred. Introducing deep learning-based approaches into the segmentation of bubble in quasi-2D fluidized beds can enhance the efficiency and reliability of data analysis. This paper addresses the current issues of long processing time and low accuracy in bubble segmentation technology in gas-solid fluidized beds by introducing a deep learning-based bubble segmentation method.

DeepLabV3+ and U-Net models are relatively widely used in various semantic segmentation models. The DeepLabV3+ model adopts a multi-scale prediction method, which can better handle objects of different scales. And the DCNN module in its encoder also supports modifying the backbone according to different task requirements, making it more flexible. The U-Net model has a shallow structure and performs better on tasks with fewer categories and simpler structures, and has been widely used in the medical field. The study utilized the DeepLabV3+ and U-Net models and trained them using quasi-2D gas-solid fluidized bed images captured by high-speed cameras under different parameter conditions. This approach aimed to obtain models suitable for quasi-2D gas-solid fluidized beds with higher accuracy. Finally, the high-accuracy model obtained is used to analyze the kinetic characteristics of iron ore powder (Geldart B particles) fluidization. This study provides a fluidized bed feature recognition approach. The conclusions will contribute to designing, operating and optimizing of fluidized bed reactors.

2. Deep learning models

Semantic Segmentation, as a fundamental task in computer vision understanding systems, involves segmenting every part of an image so that each part has a specific semantic meaning. Unlike object detection, semantic segmentation aims to outline the entire image without leaving any gaps, dividing it into different regions where each pixel is assigned to one of the predefined semantic categories for pixel-level classification prediction. It is an effective method of using computer intelligence to analyze and understand the meaning of images. Semantic segmentation is widely used in fields such as autonomous driving, medical image analysis, land parcel identification, etc (Lai et al., 2022; Maxwell et al., 2020; Wang et al., 2022; Yu et al., 2020). This study will compare the performance of five segmentation models based on DeepLabV3+

model and U-Net model, and obtain the model with the highest accuracy.

2.1. DeepLabV3+ model

The DeepLab series (including V1, V2, V3, V3+) is a classic semantic segmentation model capable of accurately segmenting different objects and areas in images in complex environments (Chen et al., 2017). It exhibits strong robustness when dealing with different types of images and scenes. Therefore, the DeepLabV3+ model is suitable for the task of bubble segmentation in gas-solid fluidized beds with high image noise and diverse bubble shapes (Chen et al., 2018).

DeepLabV3+ is the latest semantic segmentation algorithm introduced by Google in 2018. It builds upon DeepLabV3 by incorporating a simple yet effective decoder module to refine segmentation results. It has achieved promising results on various public datasets. The structure of DeepLabV3+ consists of two main components: an encoder and a decoder, as illustrated in Fig. 1.

The encoder of DeepLabV3+ consists of two main components: the DCNN backbone feature extraction network and the Atrous Spatial Pyramid Pooling (ASPP) (He et al., 2015; Jingting et al., 2013). The DCNN uses backbone models such as ResNet, Xception, MobileNet to downsample the input image and extract low-level features, outputting a low-level feature map. The ASPP module includes a 1×1 convolution, three 3×3 atrous convolutions with different dilation rates, and an upsampling structure after global average pooling back to the input size. The feature map goes through the ASPP module, where atrous convolutions with dilation rates of 6, 12, 18 run in parallel to process the feature map, resulting in five feature maps at different scales. These outputs from different dilation rates are then concatenated to produce a richer feature map, which is further dimensionally reduced through 1×1 convolutions. The dilation rate refers to the spacing between pixels that a convolution kernel corresponds to during convolution calculations, allowing for a larger receptive field with the same computational cost, meaning the pixels on the feature map correspond to larger areas on the original image. The encoder produces two outputs: a low-level feature map from the DCNN and a high-level feature map from the ASPP (Guo-bao et al., 2008).

DeepLabV3+ differs from the previous three versions of the DeepLab model in that it does not directly decode high-level features through a brute-force method of 16x upsampling. Instead, DeepLabV3+ introduces a dedicated decoder for a more refined decoding process. In the decoder part, it takes the low-level feature map from the middle layer of the DCNN and the high-level feature map from the ASPP as inputs. Firstly, the low-level feature map undergoes channel dimension reduction using 1×1 convolutions, reducing the number of channels to 48. Then, the high-level feature map from the ASPP is upsampled to match the size of the low-level feature map. The channel-reduced low-level feature map and the upsampled high-level feature map are fused and passed through a set of 3×3 convolutional layers. Finally, another upsampling step is performed to obtain a prediction map of the same resolution as the original image (Achanta et al., 2012; Bertasius et al., 2015; Chen et al., 2016; Long et al., 2015).

2.2. U-net model

U-Net. U-Net is a semantic segmentation model proposed by Ronneberger et al., in 2015 to address issues such as longer training periods and model degradation accompanying the deepening of deep learning model structures. Traditional neural models train and predict pixel by pixel, requiring vast storage space and consuming significant time. The limited neighborhood size also

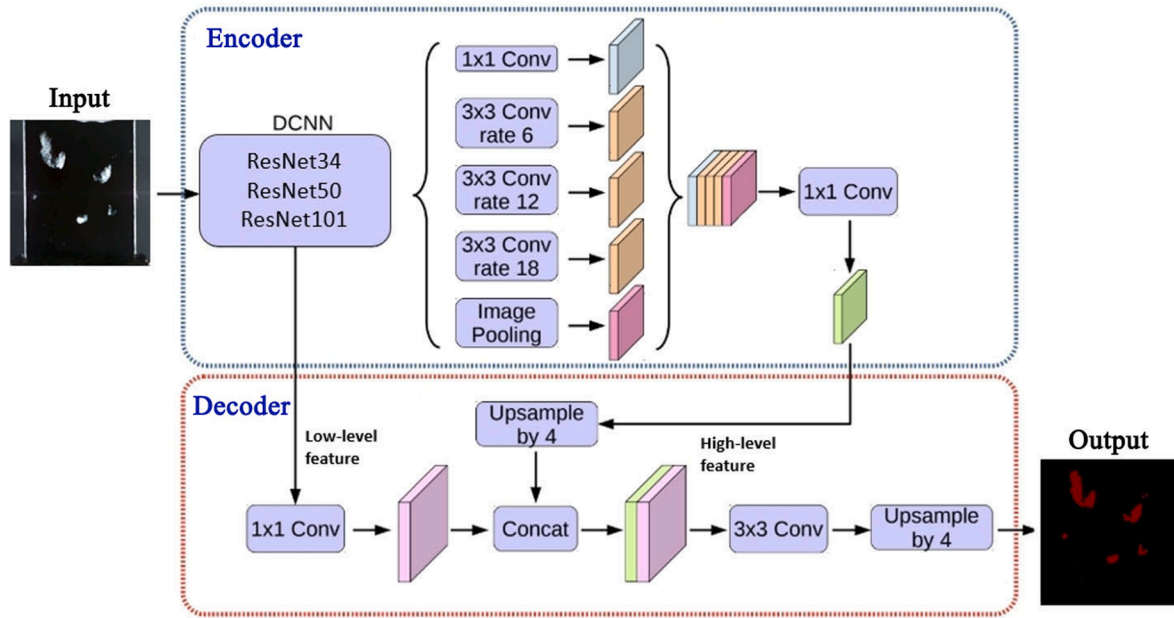


Fig. 1. DeepLabV3+ model structure.

restricts the model's receptive field, reducing its feature extraction capability. U-Net is based on Fully Convolutional Network (FCN) and is a variant of FCN (Ronneberger et al., 2015, pp. 234–241). By converting all fully connected layers into fully convolutional layers and increasing feature map dimensions through upsampling, and by connecting feature maps from different hierarchical levels through skip connections, context information fusion is achieved. This design allows the model to utilize features from both lower level er and higher levels simultaneously for image segmentation, enhancing accuracy and robustness. U-Net is considered one of the most effective and representative image segmentation models due to its outstanding performance and is widely used.

The structure of the U-Net model is shown in Fig. 2. The architecture of the U-Net model is symmetric, forming a U-shaped structure, hence its name. The model consists of an encoder, a decoder, and skip connections.

The encoder consists of layers such as convolutional layers, max pooling layers, and activation functions. It is responsible for down-sampling feature extraction of the input image. After passing through the four layers of the feature extraction network, the image obtains five effective feature maps at different levels, which will be fed into the decoder to generate the output image.

The decoder consists of convolution and upsampling methods and is responsible for image upsampling and feature fusion. Similar to the encoder, the decoder also has four layers of feature extraction networks. The network obtains feature maps through upsampling methods such as linear interpolation or transposed convolution. Subsequently, the features maps obtained from the downsampling process and the ones obtained from the upsampling process are fused through skip connections. This enrichment of context information helps the model capture clear feature

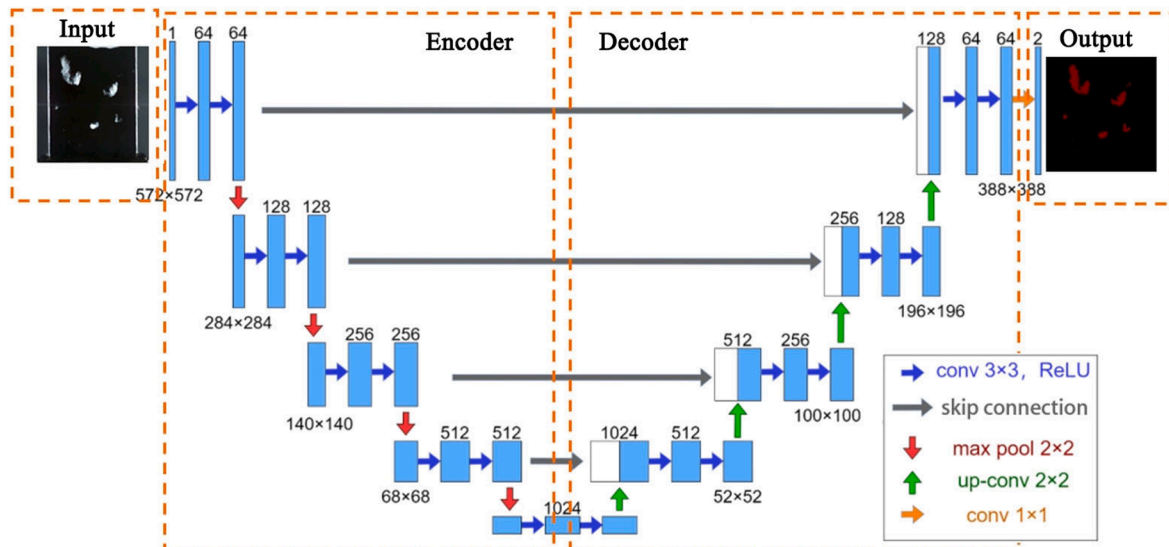


Fig. 2. U-Net model structure.

details and produce more accurate outputs until upsampled to the size of the input image, resulting in the final segmentation output.

U-Net + ResNet. Though the U-Net model effectively enhances the performance of semantic segmentation by using skip connections to link the low-level features from the encoder with the high-level features from the decoder, there is a limitation in the backbone of the U-Net model's encoder. The encoder's down-sampling backbone consists of a stack of simple CBR modules (convolutional layer + max pooling layer + ReLU activation function), which leads to the loss of some image information during forward propagation, ultimately affecting segmentation performance (Xiao et al., 2018).

In 2017, researchers proposed combining the U-Net model with the ResNet model, replacing the backbone with the more powerful learning-capable ResNet model. This resulted in a model more conducive to retaining the semantic features of images and avoiding gradient disappearance issues during the learning process. This study uses ResNet50 to replace the backbone of the U-Net model. The specific structure is shown in Fig. 3.

This study selects five models for the bubble segmentation task, including DeepLabV3+ with ResNet34, ResNet50, and ResNet101 as the backbone of encoder, the original U-Net model, and U-Net + ResNet. The accuracy of these models is compared.

3. Experiments and data preparation

Deep learning is a data-driven technology, and to obtain a model that can be used for bubble segmentation, a large amount of labeled data must be used for pre-training. In this study, labeled images of fluidized beds under different parameters are used as training data.

3.1. Experimental set-up

The schematic diagram of the quasi-2D fluidized bed is shown in Fig. 4. In order to visually observe the bubble behavior inside the bed, the bed is made of transparent acrylic sheets, with dimensions of 300 mm (height) $\times$ 100 mm (width) $\times$ 5 mm (depth). The gas distribution device consists of a 1200 mesh stainless steel sieve plate for uniform gas distribution, with a gas mixing

chamber located below the sieve plate to balance the gas flow. Compressed gas is supplied by a gas cylinder, entering the bed through a gas inlet at the bottom, and the gas flow rate is controlled using a digital flowmeter. The flow control device is a mass flow meter with a range of 50 L/min. In order to measure the pressure drop, pressure probes are installed at the inlet and outlet of the bed, to prevent particles from entering the probes and affecting the accuracy of the results. The pressure drop signal is collected by a differential pressure sensor, and directly displayed on the computer via a digital data collector system. The pressure controller and mass flow meter are both controlled by computers, and real-time data fluctuations are recorded through software.

To capture the spatiotemporal evolution of bubbles, a high-speed camera (Phantom, Model: v2012) is used to obtain synchronized images of the experimental process. Due to light obstruction from the bed material in the gas-solid fluidized bed and the requirement of bright and flicker-free lighting for the high-speed camera, a strong light is set up 80 cm behind the bed. During the experimental process, light-blocking paper is placed between the light source and the bed to avoid direct exposure. This setup ensures that the camera meets its lighting requirements, while achieving uniform light distribution to enhance the contrast between the bubble phase and the emulsion phase, eliminate bright spots in the video footage, and improve the quality of image. Each shooting is conducted after 5 min of stable fluidization of particles to obtain stable fluidization information. The shooting frequency of the high-speed camera is 200 fps, and the captured image pixels are 800×786 pixels (Covering an area of approximately 14×14 cm). Each shooting lasts for 1 min. In order to eliminate the possibility of randomness in a single experiment, three shots were taken for each operating condition.

3.2. Experimental material

In the experiment, nitrogen gas served as the fluidizing medium, while iron ore powder with diameters ranging from 0.1 to 0.2 mm and a density of 2500 kg/m^3 constituted the solid phase. The solid phase is iron ore powder with a density of 2500 kg/m^3 , and the particles are sieved using a sieve with a pore size of 0.1–0.2 mm. Subsequently, a laser particle size analyzer was used to analyze the particle size, and the average particle size of the particles was obtained to be 0.171 mm. These particles were filled to a bed height of 60 mm. Based on the distribution of pressure probes, this experiment first measured the empty bed pressure drop, and then used the descending gas velocity method to measure the pressure drop of the bed after filling with particles. The actual pressure drop is obtained by subtracting the empty bed pressure drop from the pressure drop after filling the particles, as shown in Fig. 5. The minimum fluidization velocity corresponds to a flow rate of 2.32 L/min. The detailed physical properties of the iron ore powder are listed in Table 1.

3.3. Data preparation

In five experiments conducted at different fluidization numbers (n , n is the ratio of the gas velocity U to the minimum fluidization velocity U_{mf} as in Eq. (1)) of 1.5, 2, 2.5, and 3, images of bed were captured in a completely steady state of gas-solid fluidization to eliminate the influence of particle mixing on the kinetic characteristics of the bubbles. Prior to photography, the fluidized bed had been running continuously for 3 min, ensuring the particle system had reached a fully stable state. High-speed images of the entire bed were captured using a high-speed camera. The frame rate of the camera was set to 200 fps/s, and the sampling time was set to

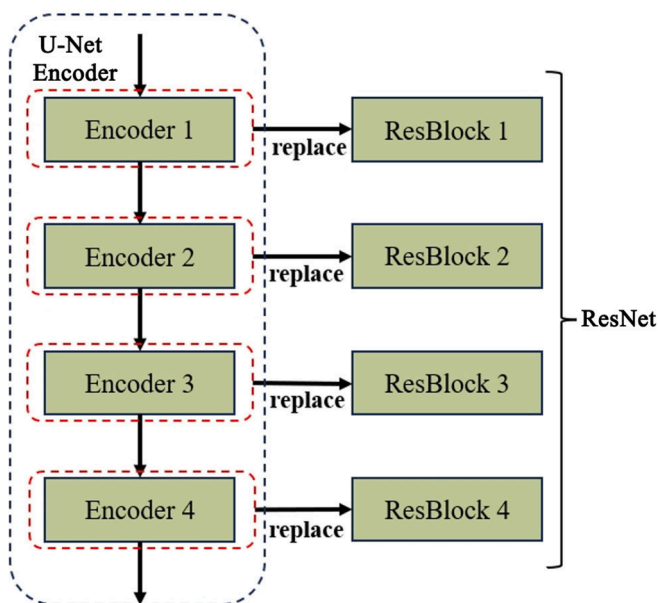


Fig. 3. U-Net + Resnet encoder structure.

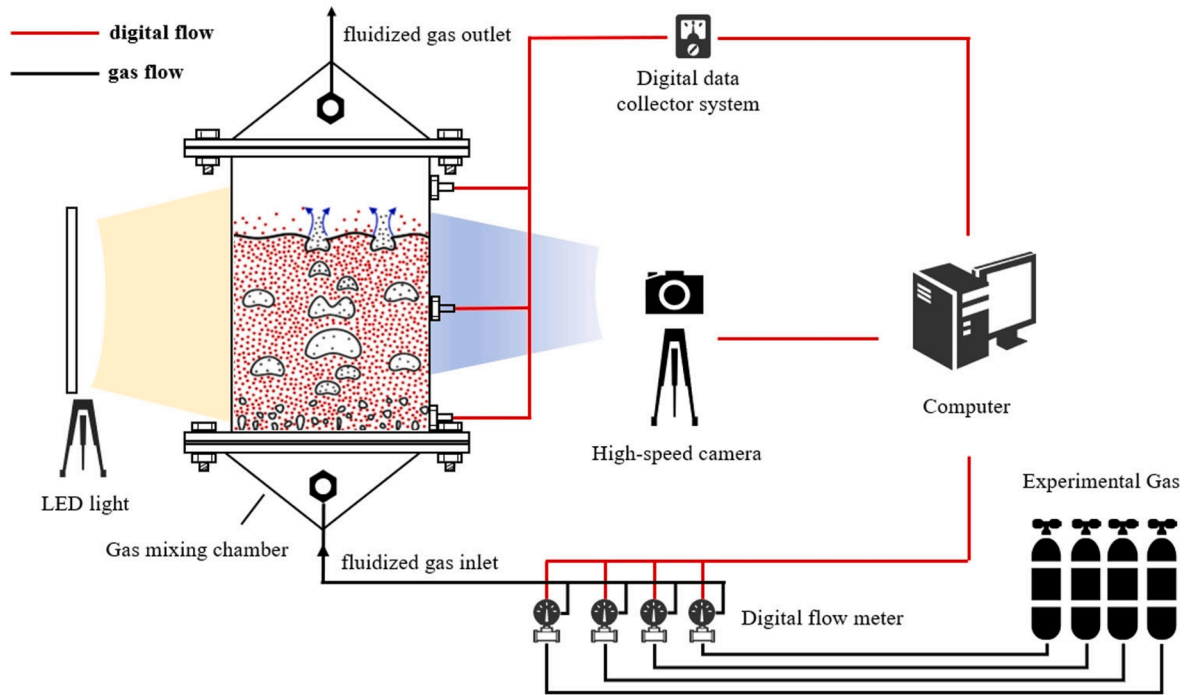


Fig. 4. Schematic diagram of quasi-2D fluidized bed.

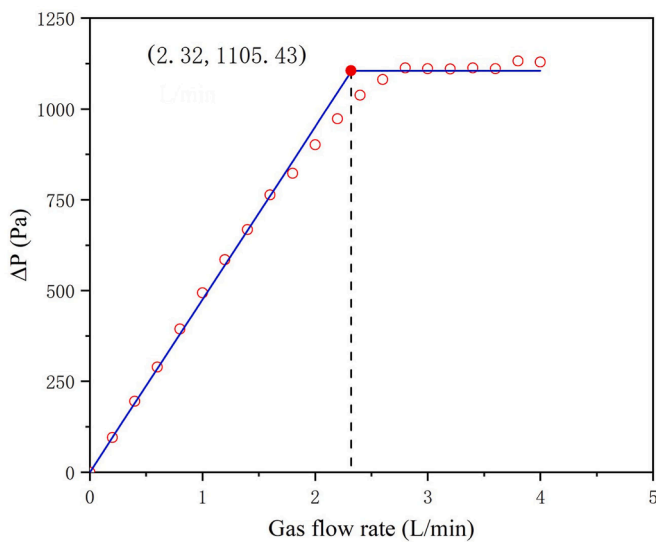


Fig. 5. Relation graph between pressure difference and gas flow rate.

30 s to ensure clear and accurate record of the bubble evolution and movement. Each frame had a resolution of 786×800 pixels. 1000 images were selected for analysis under each parameter condition.

$$n = \frac{U}{U_{mf}} \quad (1)$$

Deep learning is a data-driven technology that requires data to

be annotated before inputting into the model. The training dataset processing process is shown in Fig. 6. Using the image semantic annotation software Labelme, the bubble regions were annotated. Considering the structure of the fluidized bed and subsequent data analysis, the images were divided into two categories (bubbles and emulsion phase) for annotation. To ensure that the model learns comprehensive semantic features about bubble phase and the emulsion phase, 650 images were uniformly sampled from each set of experimental data to serve as the training and validation dataset ($n = 1.5, 2, 2.5$, and 3). These images were then annotated using Labelme software, with the bubble phase marked in red and the emulsion phase marked in green. Given the varying number of bubbles for different parameter settings, it took approximately 20 min to annotate each image on average.

Finally, the labeled data is converted into a training dataset and subjected to data augmentation techniques such as scaling, rotation, and random shuffling. 80 % of the dataset was allocated for training and the remaining 20 % for validation.

4. Segmentation performance of five deep learning network models

4.1. Evaluation metrics

The evaluation metrics consist of three fundamental indicators: Loss, pixel accuracy (PA), intersection over union (IOU), and mean intersection over union (MIOU). In the context of semantic segmentation, TP represents pixels correctly identified as the target class, TN represents pixels correctly identified as the background class, FP represents pixels incorrectly identified as the background

Table 1
Physical properties of experimental particles.

Particle type	Diameter (mm)	Density (kg/m ³)	Minimum fluidization velocity (m/s)	Minimum flow rate (L/min)
Iron ore	0.171	2500	0.077	2.32

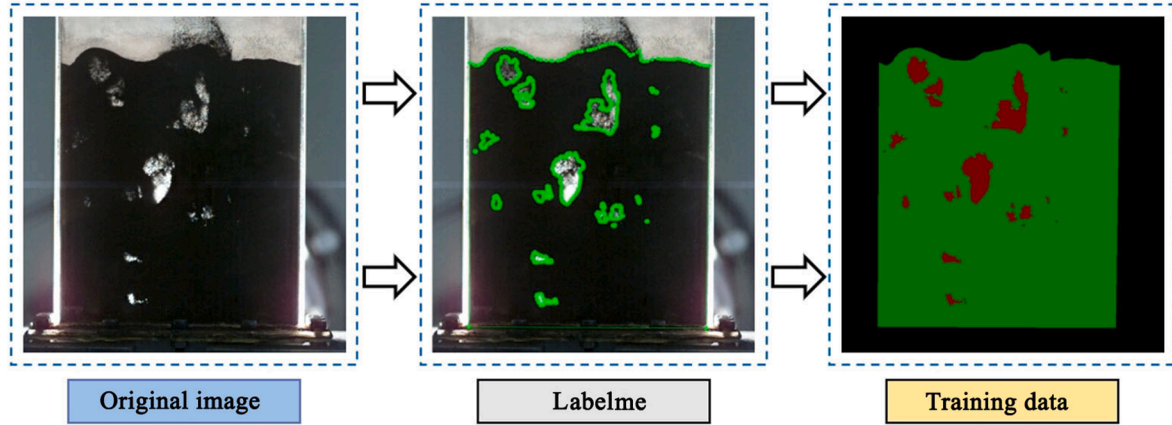


Fig. 6. Training dataset processing process.

class, and FN represents pixels incorrectly identified as the target class.

Loss. This study utilizes the CrossEntropyLoss2d loss function to compute the loss. CrossEntropyLoss2d is a variation of the cross-entropy loss function that is designed for two-dimensional data and is commonly employed in multi-class image segmentation classification tasks. It computes the sum of the cross-entropy loss between the classification results for each pixel and the actual labels, ultimately yielding the total loss value for the entire image.

For each pixel point i , the loss is calculated as Eqs. (2) and (3):

$$\text{loss}_i = - \sum_{c=1}^C y_{i,c} \log(y_{\text{pred},i,c}) \quad (2)$$

Where $y_{i,c}$ represents the true label for pixel point i and class c ; $y_{\text{pred},i,c}$ represents the model's predicted result for pixel point i and class c ; C denotes the total number of classes. This calculation is performed for each pixel point to determine the cross-entropy loss.

To calculate the average loss value for the entire image, the individual cross-entropy losses for all pixel points are averaged:

$$\text{loss} = \frac{1}{N} \sum_{i=1}^N \text{loss}_i \quad (3)$$

The final loss value, which is the cross-entropy loss for the entire image, is used to optimize the model's parameters by minimizing this loss value. By minimizing the loss function, the model's performance in image segmentation tasks can be enhanced.

Pixel accuracy. Pixel accuracy is a metric used to evaluate the performance of a model in image segmentation tasks. It refers to the consistency ratio between the pixel-level classification results produced by the model and the actual labels. Specifically, pixel accuracy is defined as the ratio of correctly classified pixels to the total number of pixels. This metric assesses the accuracy of the model at the pixel level, where a higher pixel accuracy generally indicates better performance in image segmentation tasks. The calculation formula for Pixel Accuracy is as shown in Eq. (4).

$$\text{PA} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Intersection over union. Intersection over union (IOU) is a commonly used evaluation metric in tasks such as object detection, semantic segmentation, and tracking. It is utilized to measure the overlap between classified and actual labels. IOU is defined as the ratio of the intersection and union of model's classification

results and the actual labels for a specific class. A perfect overlap between the classification results and the actual labels in an IOU of 1, while complete non-overlap yields an IOU of 0. The calculation formula for IOU is shown in Eq. (5).

$$IOU = \frac{TP}{TP + FP + FN} \quad (5)$$

Mean intersection over union. Mean intersection over union ($MIOU$) is a metric used to evaluate the performance of image segmentation tasks. It measures accuracy by calculating the overlap between the model's classification results and the actual labels. $MIOU$ is defined as the average of the IOU s for all classes in the dataset, which corresponds to the ratio of the intersection and union of the classification results and the actual labels for bubble, emulsion phase and the background. The calculation formula for $MIOU$ is shown in Eq. (6).

$$MIOU = \frac{1}{n} \sum_{i=0}^{n-1} \frac{TP}{TP + FP + FN} \quad (6)$$

Where n represents the number of classes, which is 3 in this case.

4.2. Comparative results

In the gas-solid fluidized bed, accurate segmentation of bubble is essential for studying the kinetic characteristics of bubble. In the complex environment of gas-solid two-phase flow, although there is a strong contrast between the bubble and the emulsion phase, the recognition and extraction of bubble boundaries and small bubble are challenging due to the influence of lighting and different operating conditions during image capture. Traditional image segmentation methods face difficulties in achieving accurate extraction of bubble contours due to issues such as overlapping, out-of-focus images, and uneven lighting.

To address the aforementioned issues, this study employs five deep learning-based semantic segmentation models. By harnessing the powerful feature representation learning ability of neural networks, these models utilize intelligent segmentation based on a small amount of manually annotated images to automatically capture more accurate bubble regions. The quality of the training dataset fundamentally affects the practical performance of deep learning network models. The better the quality and quantity of the data used for training, the better the model's recognition performance will be. In this work, 600 fluidized bed images under different operating conditions were used as training samples for

Table 2
Model training parameter settings.

Batch size	Optimizer	Learning rate	Weight decay	Momentum parameter
4	SGD	0.01	0.0001	0.9

the deep learning network. The relevant settings and hyper-parameters for model training are shown in Table 2. The model training uses a 4090 graphics card. The training results of different models are shown in Table 3, with the epoch where the MIOU is the highest selected as the final model. Class_IOW_0, Class_IOW_1, and Class_IOW_2 respectively represent the IOW for the background, bubble, and emulsion phase.

From Table 3, it can be seen that the DeepLabV3+ model with the ResNet50 backbone achieves optimal values for Loss (0.03406), PA (0.987), MIOU (0.93), Class_IOW_0 (0.977), and Class_IOW_2 (0.981), except for Class_IOW_1 which is slightly lower at 0.833 compared to the U-Net model's 0.836. The U-Net model with the ResNet50 backbone shows training results inferior to the original U-Net model. Therefore, based on the training results, the DeepLabV3+ model with the ResNet50 backbone performs the best.

Five different deep learning models were used for the classification study of quasi-2D fluidized bed images. The case study involved high-speed photography images of a quasi-2D fluidized bed under varying fluidization numbers, totaling 300 images. Further comparison was made on the recognition performance and noise reduction capability of the five deep learning models. The model used for testing was selected based on the highest MIOU during training. The classification results of the five models are shown in Fig. 7: (a) is the original image; (b)–(d) are the segmentation results of the DeepLabV3+ model with ResNet34, ResNet50, and ResNet101 as the backbone; (e) and (f) are the segmentation results of the U-Net model and the U-Net + ResNet50 model.

It can be observed that the DeepLabV3+ models with the ResNet34 and ResNet101 backbones, although accurately classifying bubble and emulsion phases inside the fluidized bed, tend to misclassify bed edges and external artifacts as bubble. The DeepLabV3+ model with the ResNet50 backbone demonstrates the best classification performance. This is attributed to the relatively shallow structure of the ResNet34 model, which may underperform on more complex tasks and be susceptible to interference leading to false positives. The ResNet101 model, with its overly complex architecture for a task involving a small number of categories like classifying fluidized bed bubble, can result in overfitting and require more computational resources and time. Regarding the two models based on the U-Net architecture, they exhibit more false positives when classifying the emulsion phase. Compared to the DeepLabV3+ model, the U-Net model is not well-suited for global feature extraction and semantic segmentation tasks on large-scale images. Taking everything into consideration, the DeepLabV3+ model with the ResNet50 backbone shows the best recognition performance.

Table 3
Training results of five models.

Metrics model	Loss	PA	MIOU	Class_IOW_0	Class_IOW_1	Class_IOW_2
DeepLabV3+ (Resnet101)	0.05824	0.984	0.923	0.969	0.824	0.976
DeepLabV3+ (Resnet50)	0.03406	0.987	0.93	0.977	0.833	0.981
DeepLabV3+ (Resnet34)	0.06446	0.983	0.923	0.968	0.826	0.975
U-Net	0.04947	0.983	0.926	0.966	0.836	0.975
U-Net+ (Resnet50)	0.06556	0.981	0.91	0.962	0.797	0.972

Fig. 8 shows bubble images of bubble beds processed using different methods. Among them, (a) is the original image, (b) is the deep learning image segmentation result, and (c)–(f) are binary images processed using different thresholds. Using conventional threshold segmentation methods to process images, selecting appropriate thresholds is an important reason for achieving better segmentation results. Therefore, threshold ranges of 50, 75, 100, and 150 are selected respectively.

Conventional threshold segmentation methods are usually based on the bimodal characteristics of image histograms, aiming to divide pixels in the image into bubble regions and emulsion regions by setting a fixed grayscale threshold. Generally speaking, areas with higher grayscale values in the bubble region are marked as white, while areas with relatively lower pixel values in the emulsion phase are marked as black. Fig. 8 shows that using a fixed threshold for identifying bubbles and emulsified phases is not ideal. At higher thresholds, some particles that invade larger bubbles are identified as emulsified phases, and the identified bubbles are often incomplete. In addition, shadows generated outside the bed due to factors such as static electricity and light are also identified as emulsified phases; At lower thresholds, the emulsified phase will be confused, and brighter areas formed at the edge or inside of the fluidized bed due to reflection and other reasons will be incorrectly identified as bubbles. Therefore, factors such as uneven distribution of light sources, particle impurities, and background noise can lead to errors in identifying edge bubbles using threshold methods, especially when the threshold is set too low, which can affect the final results.

Analyzing the recognition results of bubbles and emulsified phases in fluidized bed images using two methods, it can be concluded that using deep learning methods can achieve ideal recognition results. The identification results are relatively accurate for both bubbles and emulsified phases in the bed. Even with only a small number of manually annotated images, deep learning methods can still demonstrate excellent recognition performance, demonstrating their powerful learning and generalization abilities. In addition, deep learning methods effectively avoid the effects of background noise, environmental interference from fluidized bed devices, and lighting changes (such as high reflective areas or dark areas) during the experimental process.

This paper uses the DeepLabV3+ model with ResNet50 backbone to identify fluidized bed bubbles, and processes the resulting images using Python to filter out the interference of small bubbles. By inputting the image directly, it outputs parameters such as the position, area, aspect ratio, and other characteristics of the bubbles, and filters out the interference of small bubbles.

5. Bubble characteristics analysis

In this study, different fluidization numbers are set to investigate the flow state of the fluidized bed, with fluidization numbers n being 1.5, 2, 2.5, and 3. Static bed height of 6 cm. Deep learning model is employed to analyze high-speed photography images of the fluidized bed, studying the variations in fluidization characteristics under different fluidization velocities by analyzing the

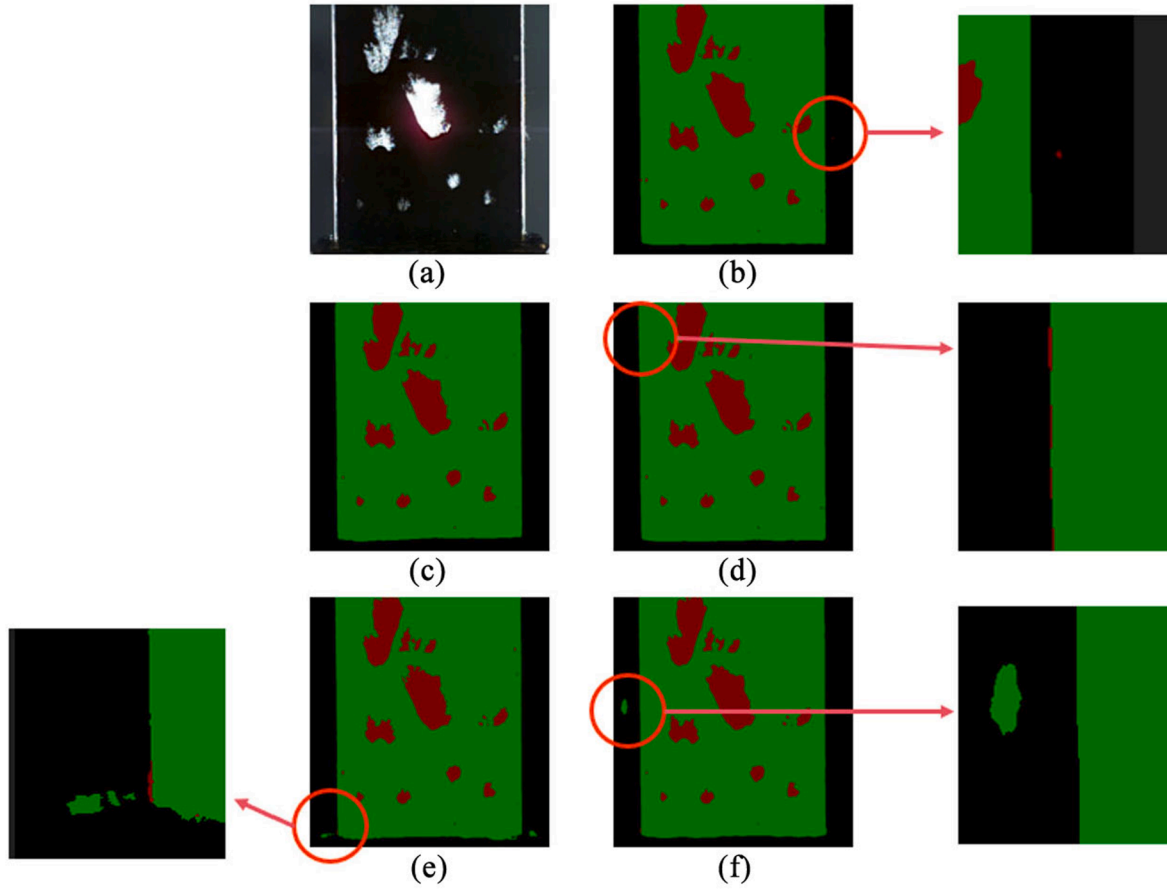


Fig. 7. Segmentation results of 5 models. (a) Original image. (b) DeepLabV3+(Resnet34). (c) DeepLabV3+(Resnet50). (d) DeepLabV3+(Resnet101). (e) U-Net. (f) U-Net + Resnet50.

size, distribution, aspect ratio, bubble velocity, and voidage. When counting bubbles, do not consider the parts closer to the bed surface, only consider bubbles within a height of 100 mm that are not connected to the outside world. Bubbles with an area less than 100 pixels (approximately 3 mm^2) are considered noise and are not included in the statistical results. The obtained data is the average of three experiments.

5.1. Bubble size and distribution

The distributions of bubble equivalent diameter as a function of the bed height are plotted in Fig. 9(a)–(e); (f) shows the distributions of bubble equivalent diameter. ($n = 1.5, 2, 2.5$, and 3). The bubble equivalent diameter bubble is defined as the diameter of a circle that is equal to the area of the bubble.

The calculation formula for the bubble equivalent diameter is shown in Eq. (7):

$$D = \sqrt{\frac{4A}{\pi}} \quad (7)$$

Where A represents the area of a standard circle equal to the area of the bubble.

Due to the bubble evolution behavior in the fluidized bed, the data as a cloud-like distribution, with the bubble size showing a trend of growth gradually along the bed height. At higher fluidization numbers, the increase in bubble equivalent diameter is more pronounced, which is consistent with physical expectations. By dividing the entire bed height into 8 intervals, the average

equivalent diameter of bubble at each height can be obtained, and plotting this data in the respective graphs can better highlight the bubble development process. The results indicate that the fluidization number has a significant impact on the equivalent diameter in the fluidized bed. The equivalent diameter becomes larger along the bed height, and the equivalent diameter becomes larger with higher fluidization numbers.

The experimental data was compared with the theoretical formula proposed by Darton and Shen in the figure. The formula is as follows:

Darton, 1977:

$$D = 0.54 \frac{(U - U_{mf})^{2/5} (H + 4\sqrt{A_0})^{4/5}}{g^{0.2}} \quad (8)$$

Shen, 2004:

$$D = \frac{0.89 [(U - U_{mf})(H + 3A_0/l)]^{2/3}}{g^{1/3}} \quad (9)$$

Where D is the bubble equivalent diameter, m; U is the gas velocity, U_{mf} is the minimum fluidization velocity, m/s; H is the distance from the sieve plate, m; A_0 is the area of the sieve plate holes, m^2 ; l is the thickness of a quasi-2D fluidized bed, m; g is the gravitational acceleration, m/s^2 . As shown in the figure, the experimental data is relatively small compared to the theoretical formula. The reason may be that the study calculated a large number of small bubbles formed by the rupture of large bubbles.

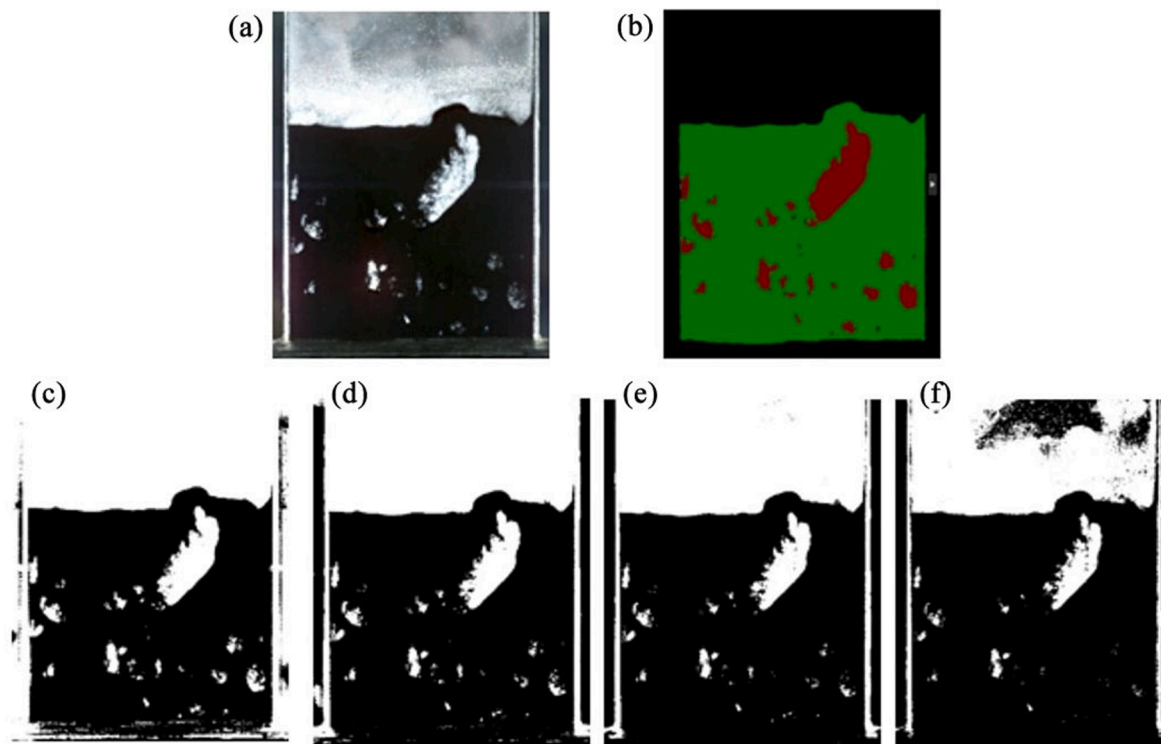


Fig. 8. Comparison of bubbling bed images processed with different thresholds and deep learning method. (a) Original image; (b) Deep learning models; (c)–(f) Threshold range 50, 75, 100, 150.

The distribution curve in the bubble equivalent diameter distribution plot shows a left-skewness unimodal distribution, which can be attributed to the large number of small bubble generated near the sieve plate and the breakup of bubble during their development. Under all fluidization numbers, the distribution of bubble equivalent diameters is almost identical. For the same particle system, the distribution of bubble equivalent diameters is not significantly influenced by the fluidization air velocity. The research results suggest that the distribution of bubble equivalent diameters is mainly influenced by factors such as the mechanism of bubble generation, bed material, fluid properties and reactor geometry, rather than the fluidization number (Busciglio et al., 2010; Yuan et al., 2023).

5.2. Bubble aspect ratio

Fig. 10(a) shows the distributions of bubble aspect ratio. The aspect ratio of a bubble is defined as the ratio of its maximum vertical extension to its maximum horizontal extension. In the fluidized bed, elongated bubbles have a greater vertical extension than their maximum horizontal extension, resulting in an aspect ratio greater than 1. Flattened bubbles have a vertical extension smaller than their horizontal extension, leading to an aspect ratio less than 1. From Fig. 10(a), it can be observed that the distribution of bubble aspect ratio exhibits a positive skewness, with the most densely populated aspect ratio being approximately equal to 1. This suggests that the vast majority of bubbles in the bed are nearly spherical with an aspect ratio equal to 1, which may primarily result from the breakup that occurs during bubble development. Analyzing the distribution curves at different fluidization numbers reveals that the bubble aspect ratio distribution remains almost unchanged. This suggests that for a fluidized bed in the

same state, the fluidization number does not significantly affect the distribution of bubble aspect ratio.

The distributions of bubble aspect ratio as a function of the bed height are plotted in Fig. 10(b). It can be observed that the bubble aspect ratio increases as the height rises for all fluidization numbers. This indicates that as the bubbles ascend, the gas content within the bubbles increases, and the bed's resistance to the gas decreases, causing the bubbles to tend to develop into elongated shapes. By examining the aspect ratio development curves at different fluidization numbers, it can be noted that there is almost no difference in the size of the bubble aspect ratio at different heights. This suggests that, for a fluidized bed under the same conditions, the fluidization number also does not significantly affect the development of the bubble aspect ratio (Caicedo et al., 2003; Liu et al., 2021).

5.3. Voidage distribution profile

In a bubbling bed, the two phases are the bubble phase and the emulsion phase. It is assumed that the voidage of bubble phase is 1 and the voidage of emulsion phase is 0. The bed voidage can be considered as the ratio of the bubble area to the total bed area. The variation of the voidage in the bubbling bed reflects changes in the bubble state. To study the effect of fluidization number on the bubbling behavior of the fluidized bed, a 20 mm region of interest was selected at different heights. Fig. 11 shows the variation of voidage over time within 20–40 mm from the sieve plate at different fluidization numbers ($n = 2, 3$). Fig. 12 shows the variation of voidage over time within 0–20 mm, 20–40 mm and 40–60 mm from the sieve plate at $n = 2$.

From Fig. 11, it can be observed that the bed voidage fluctuates significantly over time, and this fluctuation is mainly influenced by the coalescence and breakup of the bubbles. At the same height, an

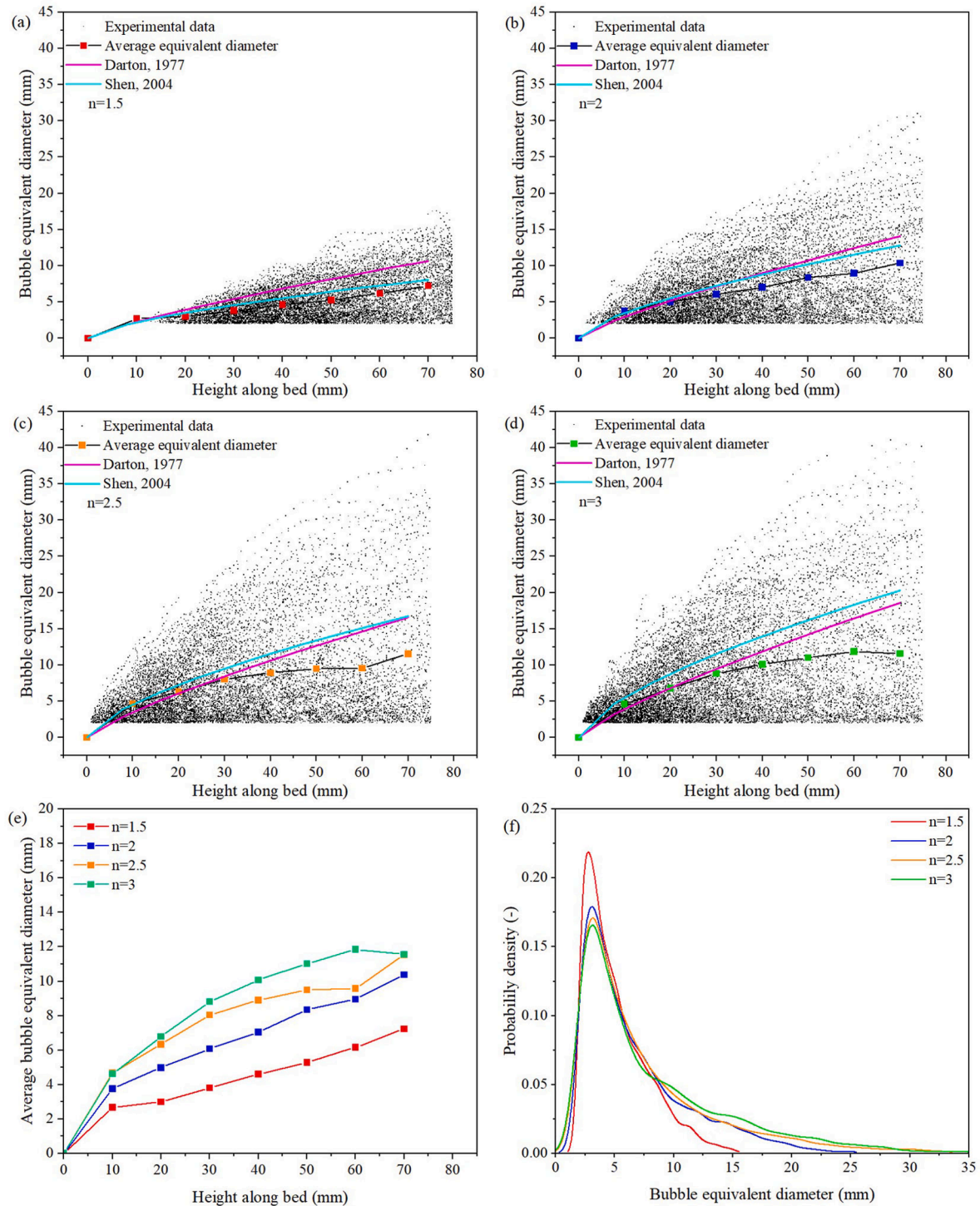


Fig. 9. (a)–(d) Bed height dependence of the bubble equivalent diameter with arithmetic average data. (e) Bed height dependence of the average bubble equivalent diameter. (f) Probability density plot of bubble equivalent diameter.

increase in fluidization number leads to larger bubble sizes and more bubbles, resulting in a greater voidage. The gas exchange becomes more rapid, and the coalescence and breakup of bubbles occur more frequently, leading to a larger standard deviation of the voidage (Yuan et al., 2023).

Under the same fluidization number, the small bubbles in the bed are either coalesced by larger bubbles from above or the

bubbles in the bed breakup, both of which can cause a decrease in the voidage. Conversely, the completion of coalescence by larger bubbles will result in an increase in the voidage. According to the average value and standard deviation of the voidage shown in Fig. 12, it can be seen that at positions closer to the sieve plate, the average value and standard deviation of the voidage are smaller, indicating that the bubbles in this region are generally

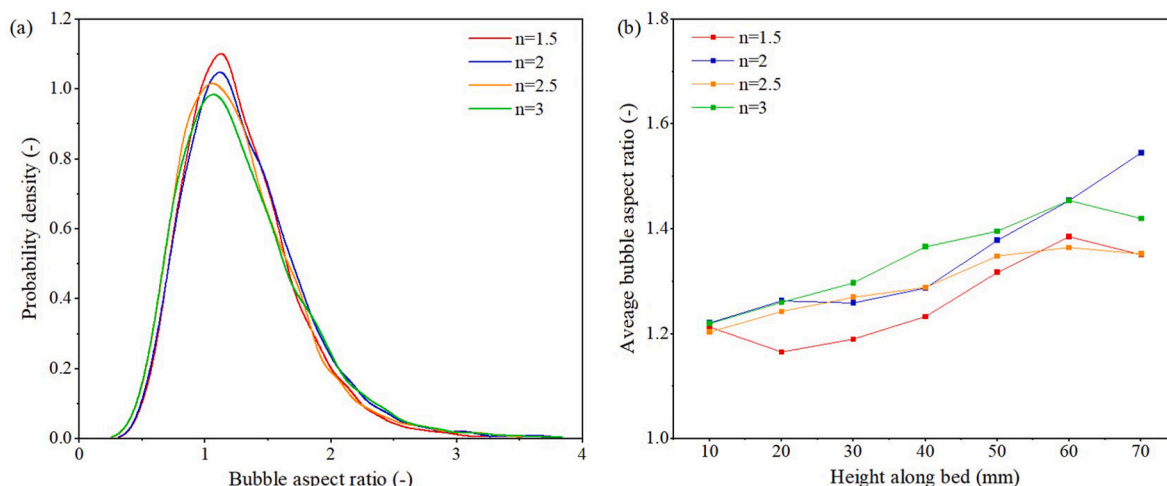


Fig. 10. (a) Probability density plot of bubble aspect ratio. (b) Bed height dependence of the average bubble aspect ratio.

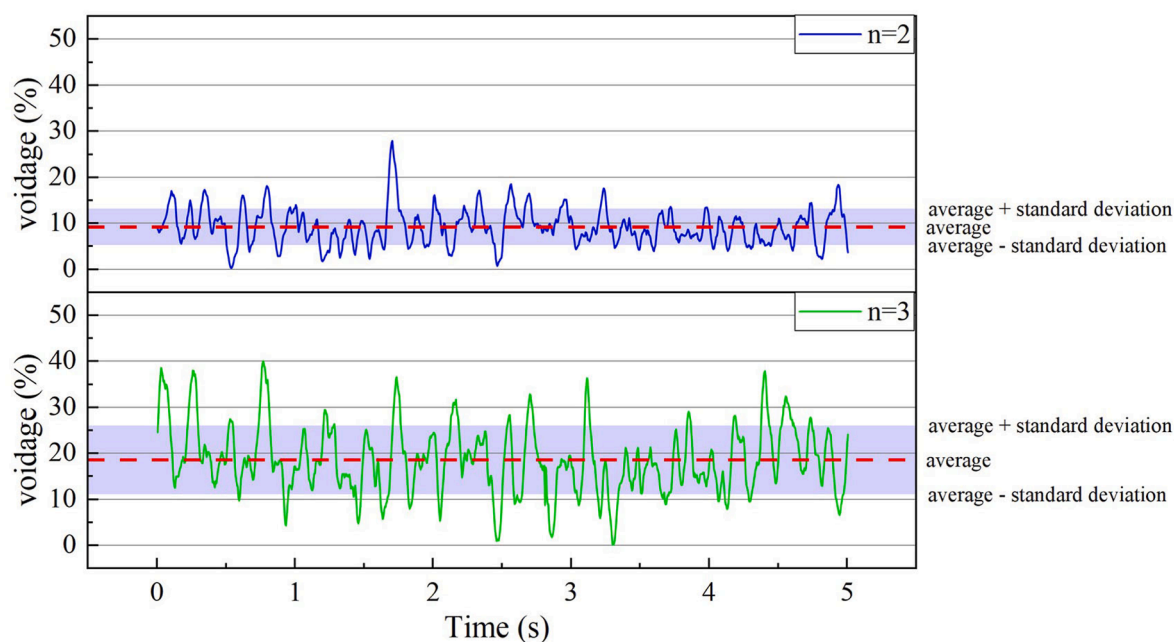


Fig. 11. Voidage profile within 20–40 mm from the sieve plate ($n = 2, 3$).

smaller, and the frequency of bubble coalescence and breakup is low, leading to a relatively stable bed. As one moves closer to the surface of the bed, both the average value and standard deviation of the voidage increase, indicating a higher frequency of bubble coalescence and breakup in the bed, resulting in greater disturbances and reduced stability of the bed.

5.4. Bubble rising velocity

When calculating the rising speed of bubbles, the program matches the bubbles based on their aspect ratio, distance, and size in two frames of images. Firstly, set a larger threshold. If the aspect ratio, distance, and size do not exceed the threshold, it is considered as the same bubble. Check if the result is incorrect. If there are errors, gradually lower the threshold until the result is correct.

The distributions of bubble rising velocity as a function of bubble equivalent diameter are plotted in Fig. 13(a)–(d). The bubble rising velocity is defined as the speed at which bubbles move vertically upwards along the reactor.

Overall, the data points for bubble rising velocity are widely scattered. By dividing the entire range of bubble equivalent diameters into seven intervals, the average bubble rising velocity for each equivalent diameter can be obtained and plotted in the corresponding graphs. The average bubble rising velocity data show a clear upward trend, indicating that the bubble rising velocity increases with the increase of bubble equivalent diameter. It can be inferred that the distribution of bubble rising velocity data points extends toward the upper right, and the widely scattered data points is caused by complex bubble motion such as coalescence and breakup. All average bubble rising velocity data across different fluidization numbers have been plotted in Fig. 13(e). It

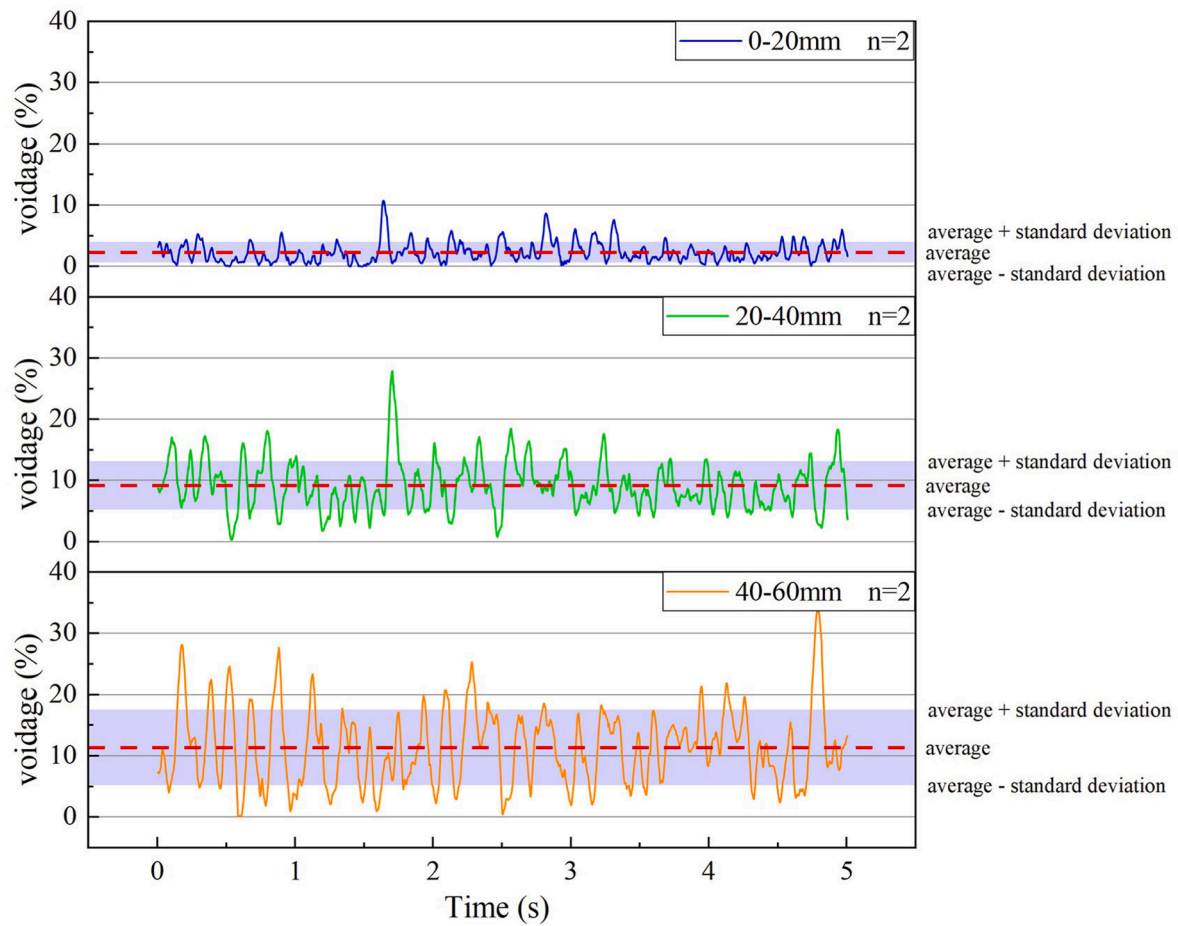


Fig. 12. Variation of voidage within 0–20 mm, 20–40 mm, 40–60 mm from the sieve plate at $n = 2$.

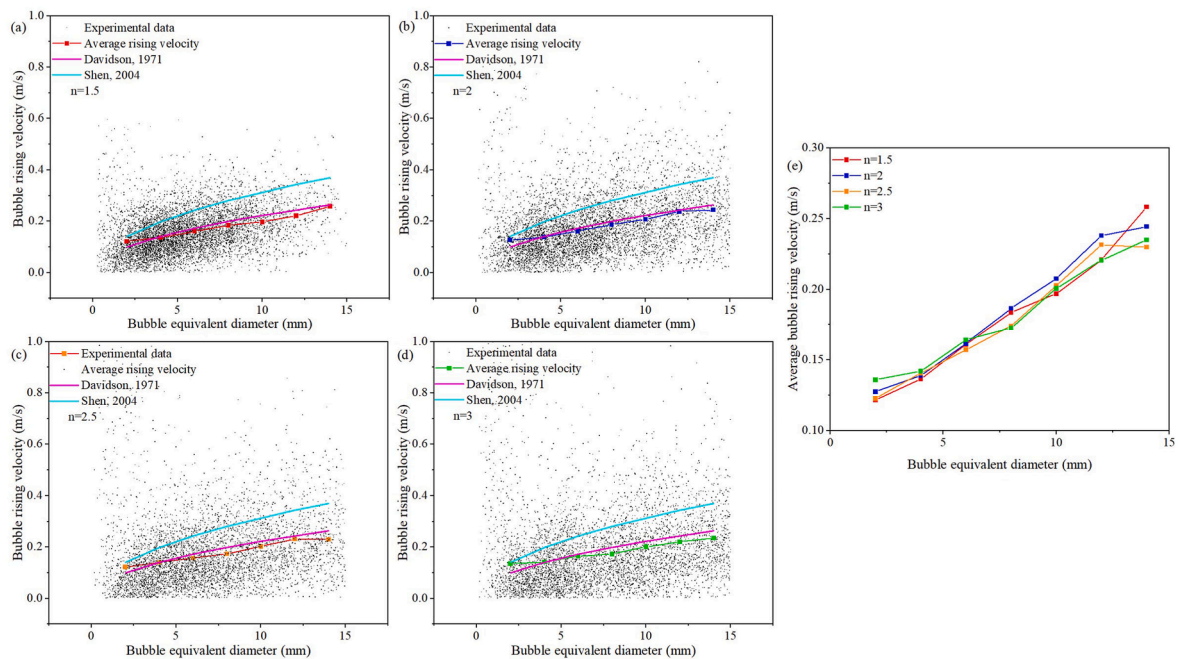


Fig. 13. (a)–(d) Bubble equivalent diameter dependence of the rising velocity with arithmetic average data. (e) Bubble equivalent diameter dependence of the average rising velocity.

can be seen that there are no significant differences in average bubble rising velocity for different bubble equivalent diameters. This indicates that, under the same conditions in the fluidized bed, the rising velocity of bubbles of the same size is independent of fluidization number.

Draw the theoretical formula for the variation of rising speed with equivalent diameter in the figure.

$$u = \phi \sqrt{gD} \quad (10)$$

Where u is the bubble rising velocity, m/s; ϕ is the velocity coefficient. Davidson and Shen respectively consider ϕ to be 0.71 and 1.0. It can be seen that the correlation obtained from the study is very consistent with the theoretical formula. And it is closer to what Davidson proposed.

6. Conclusion

This study evaluates the segmentation performance of five deep learning network models in the task of bubbles segmentation in a quasi-2D fluidized bed. Additionally, various kinetic characteristics of the fluidized bed, including bubble equivalent diameter and distribution, bubble aspect ratio, bed voidage, and bubble rising velocity, were obtained using deep learning model. In summary, the conclusions of this study are listed as follows:

- (1) The DeepLabV3+ model with the ResNet50 backbone achieves optimal values for Loss, PA, MIOU, Class_IOU_0, and Class_IOU_2, except for Class_IOU_1 which is slightly lower compared to the U-Net model. Based on the training results, among the five models, the DeepLabV3+ model with Resnet50 performs the best.
- (2) The fluidization number has a significant impact on the development and size of bubble equivalent diameter in the fluidized bed. The average equivalent diameter generally increases with bed height, and with higher fluidization numbers, the bubbles grow faster.
- (3) For identical particle systems, variations in fluidization number have minimal impact on both bubble size distribution and aspect ratio distribution. The distribution curve of the equivalent diameter of the bubbles shows a left-skewed unimodal distribution; the aspect ratio distribution exhibits a positive skewness, with the most frequently occurring aspect ratio approximately equal to 1. This indicates that small nearly spherical bubbles are predominant.
- (4) Voidage within the fluidized bed increases as both fluidization number and height from the sieve plate rise. As these parameters increase so do both bubble size and quantity leading to enhanced gas-solid exchange rates. Consequently, this results in more frequent coalescence and breakup of bubbles which destabilizes the bed while causing greater fluctuations in voidage.
- (5) Bubble rising velocity correlates positively with increasing bubble equivalent diameter. Under consistent conditions within a given fluidized bed system, the rising velocity of similarly sized bubbles remains independent of changes in fluidization number.

CRedit authorship contribution statement

Yuchen Liu: Validation, Data curation. **Chuanhao Wang:** Software. **Shiyuan Li:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project

administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

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

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