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Artificial Intelligence Assists In The Analysis Of The Characteristics Of Chemical Micro-dispersed Multiphase Flow Fields And The Characterization Of Fundamental Mechanisms

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Abstract: Interfacial dynamics play a critical role in determining the performance of chemical micro dispersed multiphase flow systems, while accurate characterization of transient interface evolution remains challenging due to complex morphology and rapid deformation. This study develops an artificial intelligence assisted framework for quantitative characterization of interfacial dynamics by integrating high resolution flow visualization, deep learning based interface identification, and geometric descriptor analysis. The proposed framework automatically extracts interface boundaries from experimental images and converts visual information into quantitative parameters, including interface length, curvature, and droplet morphology characteristics. The results demonstrate that the artificial intelligence approach provides reliable interface identification under different flow conditions and enables continuous analysis of dynamic interface evolution. Furthermore, explainable analysis reveals that the model mainly focuses on physically meaningful regions associated with interface boundaries and deformation characteristics. The developed framework provides a systematic approach for linking image based observations with quantitative multiphase flow analysis and offers potential applications in microreactors, emulsification, mixing processes, and intelligent process monitoring.

Keywords: Artificial intelligence; Multiphase flow; Interfacial dynamics; Image analysis; Deep learning; Micro dispersed flow

1 Introduction

Chemical micro-dispersed multiphase flows are fundamental to many chemical engineering processes, including microreactors, emulsification, extraction, catalytic reactions, pharmaceutical manufacturing, and advanced material preparation. In these systems, the interaction between different phases determines the efficiency of mass transfer, heat transfer, chemical reactions, and product quality. Among the various flow characteristics, the evolution of the fluid interface is one of the most important factors because it directly influences droplet formation, deformation, breakup, coalescence, and dispersion. Consequently, accurate characterization of interfacial dynamics is essential for understanding transport phenomena and improving process performance in modern chemical engineering systems (Cao et al., 2024).

Recent advances in experimental visualization technologies have significantly improved the observation of complex multiphase flow behavior. High speed imaging, micro particle image velocimetry, laser induced fluorescence, and other optical measurement techniques enable researchers to capture transient interface evolution with high spatial and temporal resolution. These experimental approaches generate large quantities of image data that contain abundant information about interface morphology and flow evolution. At the same time, numerical simulation methods have become increasingly powerful for reproducing complex multiphase transport processes. Together, experimental measurements and computational simulations provide valuable information for investigating interfacial phenomena. However, the increasing volume and complexity of flow field data also present new challenges for quantitative analysis and efficient interpretation (Zhang et al., 2023).

Although substantial progress has been achieved in experimental observation and numerical simulation, quantitative characterization of interfacial dynamics remains a challenging task. Chemical micro-dispersed multiphase flows exhibit strong nonlinearity, rapid temporal variation, and complex interface deformation. The morphology of fluid interfaces continuously changes under the combined influence of inertial forces, viscous forces, surface tension, and local flow disturbances. As a result, interface boundaries are often irregular and highly dynamic. Conventional analysis methods frequently encounter difficulties when processing large image datasets containing blurred boundaries, overlapping droplets, or nonuniform illumination. These limitations reduce the reliability and consistency of quantitative measurements, particularly under complicated operating conditions.

Artificial intelligence has recently become an important technology for processing large scale engineering data. Deep learning methods have demonstrated remarkable capability in image recognition, semantic segmentation, feature extraction, and pattern analysis. These advantages have promoted the application of artificial intelligence in various fields of chemical engineering, including process monitoring, fault diagnosis, intelligent manufacturing, and computational fluid dynamics (Siavashi et al., 2024). Artificial intelligence also provides new opportunities for analyzing complex multiphase flow images because it can automatically identify image features and reduce the dependence on manually designed algorithms (Yuan et al., 2024).

Despite these developments, current applications of artificial intelligence in multiphase flow research mainly emphasize prediction and recognition tasks. Existing studies generally focus on flow pattern classification, bubble detection, droplet identification, pressure prediction, or surrogate modeling (Zhu et al., 2020; Siavashi et al., 2024) . These studies have

demonstrated that artificial intelligence can improve computational efficiency and recognition accuracy. However, they provide limited support for quantitative characterization of interfacial dynamics. In many cases, artificial intelligence functions primarily as a prediction tool rather than as an analytical framework for understanding interface evolution. Consequently, the physical significance of automatically learned image features remains insufficiently explained, and the relationship between image characteristics and interface evolution is still not well established (Brasse et al., 2023).

Another important challenge concerns the quantitative description of interface evolution. Interfacial dynamics involve continuous variations in interface geometry rather than isolated changes at individual time points. Parameters such as interface length, interface curvature, droplet diameter, circularity, and aspect ratio evolve simultaneously during deformation, stretching, breakup, and coalescence (Theisen et al., 2023). These parameters are physically meaningful because they reflect the dynamic response of the interface to changing flow conditions. Nevertheless, existing studies usually investigate these descriptors independently or focus on a limited number of geometric measurements. A unified framework that automatically extracts representative interfacial features, quantitatively describes their temporal evolution, and relates these changes to flow behavior is still lacking.

Furthermore, increasing attention has been directed toward the interpretability of artificial intelligence in scientific research. High prediction accuracy alone is often insufficient for engineering applications because researchers also need to understand why a model reaches a particular conclusion. Explainable artificial intelligence offers the possibility of identifying influential image features and providing visual evidence for model decisions (Nie et al., 2022). This capability is particularly valuable for multiphase flow analysis because it can establish meaningful connections between image information and physical interface evolution. Therefore, improving the physical interpretability of artificial intelligence has become an important direction for intelligent engineering analysis (Yang et al., 2023).

Based on the above considerations, the central scientific question addressed in this study is as follows: How can artificial intelligence be used to quantitatively characterize interfacial dynamics in chemical micro-dispersed multiphase flows while maintaining physical interpretability? This question extends beyond improving image recognition accuracy. Instead, it focuses on developing a systematic analytical framework that transforms complex flow images into physically meaningful quantitative information. Solving this problem is expected to improve the understanding of interface evolution and provide more reliable support for intelligent analysis of multiphase transport processes.

Accordingly, the primary objective of this study is to develop an artificial intelligence assisted framework for the quantitative characterization of interfacial dynamics in chemical micro-dispersed multiphase flows. Specifically, this study seeks to achieve three objectives. The first objective is to improve the automatic identification of complex fluid interfaces from high speed flow images. The second objective is to establish a quantitative characterization strategy for describing the temporal evolution of representative interfacial characteristics under different operating conditions. The third objective is to enhance the physical interpretability of interface analysis by incorporating explainable artificial intelligence to identify the image features that contribute most significantly to interface evolution.

The proposed framework emphasizes quantitative characterization rather than prediction alone. Instead of treating artificial

intelligence as a black box, the framework combines automatic image analysis with physically meaningful feature extraction and interpretable model analysis (Kuang et al., 2021). This strategy provides a direct connection between interface morphology and flow behavior, thereby supporting more reliable engineering interpretation. The framework is expected to improve the efficiency and consistency of interface analysis while reducing the dependence on manual image processing and subjective parameter selection.

This study makes three principal contributions. First, it proposes an integrated artificial intelligence assisted framework for quantitative characterization of interfacial dynamics in chemical micro-dispersed multiphase flows (Nizovtseva et al., 2024). Second, it establishes a unified quantitative characterization strategy that describes the temporal evolution of interfacial morphology through multiple physically meaningful descriptors. Third, it incorporates explainable artificial intelligence to establish physically interpretable relationships between learned image features and interface evolution. These contributions provide a practical methodology for intelligent interface analysis and offer a data driven foundation for future research on multiphase flow characterization, process optimization, and intelligent chemical engineering systems.

2. Conceptual Framework

Interfacial dynamics are fundamental phenomena governing the performance of chemical micro dispersed multiphase flow systems. During multiphase transport, fluid interfaces continuously undergo deformation, stretching, breakup, and coalescence due to the interaction between hydrodynamic forces and interfacial tension. These processes directly influence mass transfer, mixing efficiency, reaction performance, and product quality. Therefore, accurate characterization of interface evolution is essential for understanding complex multiphase transport mechanisms and improving chemical process design (Wang et al., 2022).

Recent advances in high speed imaging and optical measurement techniques have significantly improved the observation of transient multiphase flow behavior. Experimental methods can now capture detailed interface evolution, including droplet deformation, local instability, and breakup processes. However, the increasing resolution and data volume of experimental images have created new challenges for quantitative analysis (Shen et al., 2020). The main difficulty is no longer image acquisition, but the extraction of meaningful physical information from large and complex image datasets (Chen et al., 2023).

Conventional image processing methods have been widely applied for interface identification. Threshold segmentation, edge detection, and morphological operations provide practical solutions for extracting interface boundaries from experimental images. However, these approaches mainly rely on predefined rules and manual parameter adjustment. Their performance can be affected by illumination variation, image noise, weak interface contrast, and complex deformation. As a result, conventional methods often struggle to provide stable and continuous characterization when interface morphology changes dynamically(Cerqueira & Paladino, 2021) .

In addition, traditional approaches usually focus on individual geometric measurements, such as droplet diameter or interface perimeter. Although these parameters provide useful information, interfacial dynamics involve simultaneous changes in multiple

geometric characteristics. Interface stretching, local deformation, and droplet shape transition cannot be fully described by a single parameter. Therefore, a comprehensive characterization framework requires the integration of multiple descriptors that can represent different aspects of interface evolution.

Artificial intelligence has recently provided new possibilities for analyzing complex scientific images. Deep learning models can automatically extract representative spatial features from experimental data without relying on manually designed rules (Minaee et al., 2022). In engineering applications, artificial intelligence has demonstrated strong capabilities in image segmentation, object recognition, and feature extraction. These advantages have encouraged increasing applications of artificial intelligence in multiphase flow analysis, particularly for identifying bubbles, droplets, and complex interface structures (Minaee et al., 2022).

However, current artificial intelligence applications in multiphase flow research mainly focus on recognition accuracy or prediction performance. Most studies evaluate models using computational indicators, such as accuracy, precision, recall, and intersection over union. Although these metrics demonstrate algorithmic capability, they provide limited information regarding the physical meaning of extracted features. A reliable scientific framework should not only identify interfaces accurately but also explain how image features relate to interface evolution and flow behavior (Soibam et al., 2023).

Based on this research gap, this study proposes an artificial intelligence assisted conceptual framework for quantitative characterization of interfacial dynamics in chemical micro dispersed multiphase flows. The framework extends artificial intelligence beyond image recognition by integrating interface identification, quantitative descriptor extraction, temporal evolution analysis, and explainable feature interpretation. The overall framework is illustrated in Figure 1.

As shown in Figure 1, the proposed framework consists of six interconnected stages. The first stage is experimental image acquisition, where high speed imaging is used to capture continuous interface evolution under controlled flow conditions (Shorten & Khoshgoftaar, 2021). Unlike conventional analysis based on selected representative images, the proposed framework considers sequential image information to preserve temporal characteristics.

The second stage is artificial intelligence based interface identification. Experimental images are transformed into reliable interface representations through automated segmentation. This stage reduces the dependence on manual processing and provides consistent interface boundaries for further analysis.

The third stage is quantitative descriptor extraction. Based on the identified interface boundaries, representative parameters, including interface length, curvature, droplet diameter, circularity, and aspect ratio, are calculated to describe different aspects of interfacial behavior. These descriptors provide a multidimensional representation of interface evolution rather than a single geometric measurement(Isensee et al., 2021) .

The fourth stage is temporal analysis of interfacial dynamics. The extracted descriptors are analyzed under different flow conditions to characterize deformation, stretching, and morphological transition processes. Through this stage, artificial intelligence becomes a quantitative analytical approach rather than only an image recognition method.

The fifth stage introduces explainable artificial intelligence analysis. Attention visualization and feature contribution analysis are used to identify image regions that influence model decisions. This stage establishes a connection between AI derived features and physically meaningful interface characteristics.

The final stage is physical interpretation of interfacial evolution. The quantitative descriptors and explainable AI results are integrated to understand the relationship between interface morphology and flow behavior. Therefore, the proposed framework provides both computational analysis and physical interpretation.

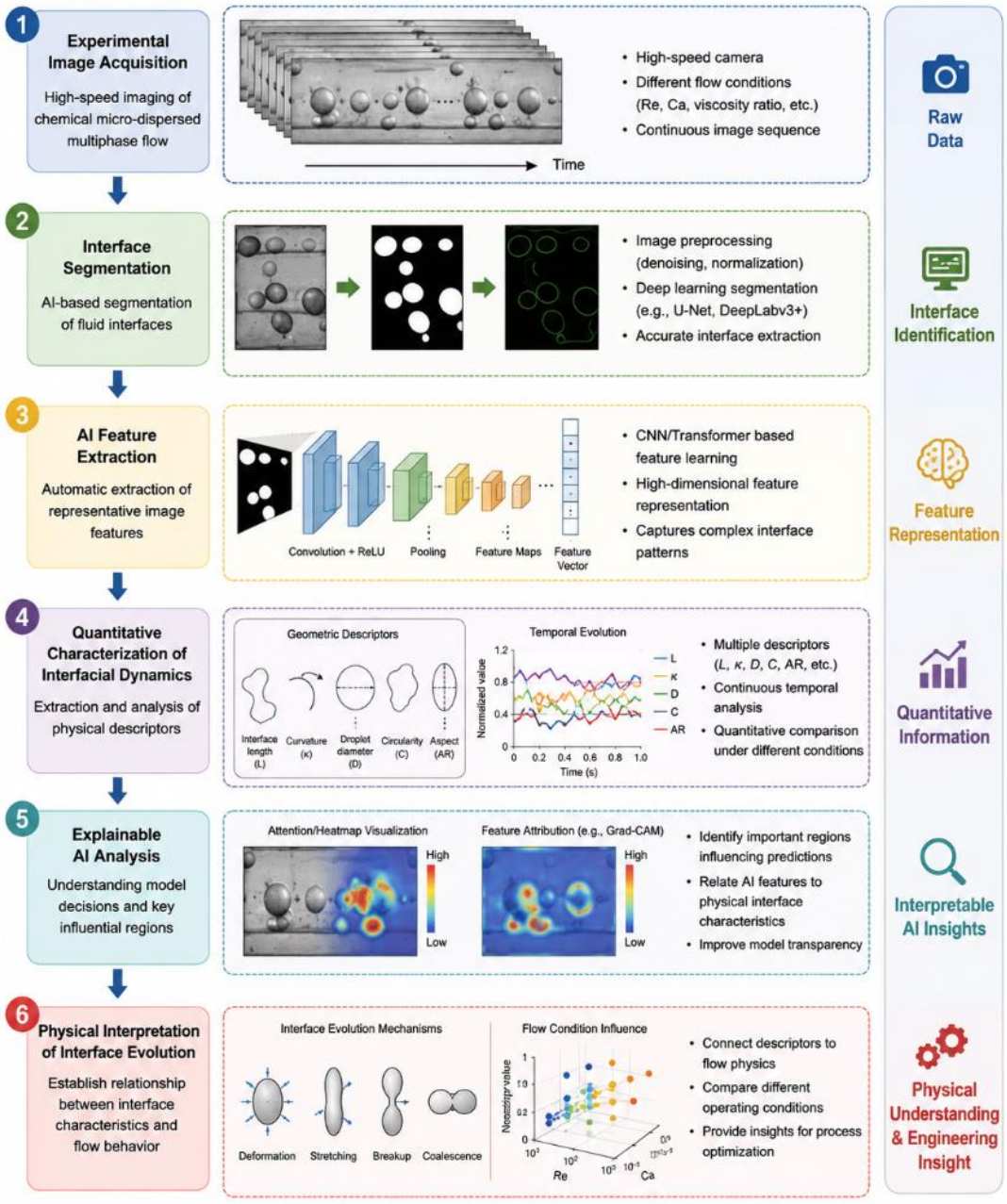

Figure 1. Conceptual framework of the proposed artificial intelligence assisted quantitative characterization of interfacial dynamics in chemical micro dispersed multiphase flows

3 Materials and Methods

3.1 Experimental System

The experimental system was established to generate and visualize chemical micro dispersed multiphase flows under controlled operating conditions. The main purpose of the experimental platform was to obtain high quality interface images with sufficient spatial and temporal resolution for subsequent quantitative characterization. The system consisted of a fluid delivery unit, a transparent microfluidic flow channel, an optical visualization unit, and a data acquisition system. The overall configuration of

the experimental platform is illustrated in Figure 2.

The fluid delivery unit consisted of two precision syringe pumps that independently controlled the flow rates of the continuous phase and dispersed phase. The two phases were introduced into a transparent T junction microchannel, where the interaction between the phases generated dispersed droplets and continuously evolving interfaces (Samek et al., 2021). The use of a transparent observation section allowed direct visualization of interface deformation, droplet formation, and transport behavior without disturbing the flow field. The experimental configuration was designed to provide stable flow generation and minimize external disturbances during image acquisition.

A high speed imaging system was used to record the transient evolution of the fluid interface. The camera was positioned perpendicular to the observation region to reduce optical distortion and maintain consistent image quality. A uniform LED illumination system was applied to improve interface contrast and enhance the separation between the dispersed phase and continuous phase. The imaging parameters, including frame rate, exposure time, and spatial resolution, were adjusted according to the characteristic time scale of interface evolution. The acquired images were stored in a lossless format to preserve boundary information and original image characteristics for further analysis.

Before each experiment, the microchannel and connecting tubes were cleaned to remove residual fluids and possible contaminants. The flow system was then filled gradually to eliminate trapped air and ensure stable operation. After the multiphase flow reached a steady state, image recording was initiated. For each operating condition, continuous image sequences were collected to capture the complete evolution of the interface rather than individual static images. Multiple experimental repetitions were performed under identical conditions to improve data reliability and reduce the influence of random experimental variation.

The operating conditions were selected based on the characteristic parameters governing multiphase interface behavior. The inlet flow rates of both phases were adjusted systematically to generate different flow conditions. Dimensionless parameters, including Reynolds number, Weber number, and Capillary number, were calculated to describe the relative effects of inertia, surface tension, and viscous forces. The detailed experimental conditions are summarized in Table 1. These parameters provide a consistent basis for comparing interface evolution under different flow states.

The experimental system provides a reliable platform for obtaining reproducible multiphase flow images and quantitative interface information. Similar visualization based experimental systems have been widely applied in recent multiphase flow studies because they enable direct observation of transient interface behavior and provide valuable data for advanced image analysis methods (Chen et al., 2023; Wang et al., 2022). The experimental dataset generated from this platform was subsequently used for artificial intelligence assisted interface identification and quantitative characterization of interfacial dynamics.

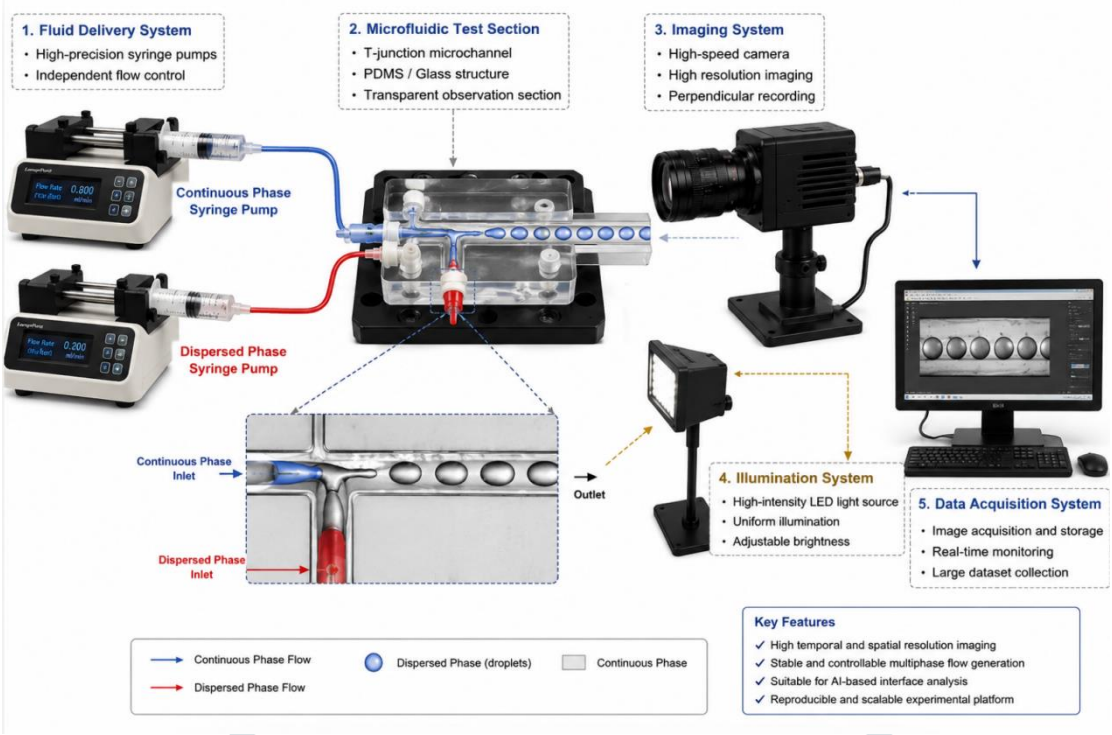

Figure 2. Experimental platform for visualization and image acquisition of chemical micro dispersed multiphase flows

Table 1. Experimental operating conditions for image acquisition

Parameter	**Symbol**	**Value Range**	**Unit**
Continuous phase flow rate	Qc	0.20–1.20	mL min^{-1}
Dispersed phase flow rate	Qd	0.05–0.60	mL min^{-1}
Reynolds number	Re	5–120	–
Weber number	We	0.10–8.00	–
Capillary number	Ca	0.001–0.080	–
Operating temperature	T	25 ± 1	°C
Camera frame rate	f	1000–5000	fps
Image resolution	–	2048 × 2048	pixels
Exposure time	t_e	20–200	μs
Number of images per condition	N	≥3000	images

3.2 AI-assisted Image Analysis

The artificial intelligence assisted image analysis procedure was developed to automatically identify fluid interfaces from the experimental image dataset and provide standardized interface representations for subsequent quantitative characterization. The purpose of this procedure was to reduce the dependence on manual image processing and establish a consistent approach for extracting interface information from complex multiphase flow images. The complete workflow of the artificial intelligence based image analysis process is presented in Figure 3, which includes image preprocessing, dataset preparation, model training, model validation, interface segmentation, and generation of segmentation outputs.

The original experimental images were first processed through a standardized preprocessing procedure to improve data consistency before model training. Image preprocessing included image normalization, size adjustment, and intensity correction. These operations reduced the influence of variations in illumination conditions and ensured that all images had identical input dimensions. The preprocessing procedure was applied uniformly to the complete image dataset to maintain consistency between training samples and independent testing samples. No artificial modification was introduced that could change the original interface morphology.

After preprocessing, the image dataset was prepared for supervised deep learning. Pixel level annotation was performed to generate reference interface masks, where each pixel was assigned according to whether it belonged to the fluid interface region or the background region. The annotated dataset was randomly divided into training, validation, and testing subsets. The training dataset was used for model parameter optimization, while the validation dataset was used to monitor the learning process and prevent overfitting. The independent testing dataset was reserved for evaluating the final model performance. This separation ensured that the trained model was assessed using image samples that were not involved in parameter adjustment.

A convolutional neural network based semantic segmentation model was adopted to perform interface identification. The model was selected because semantic segmentation networks have demonstrated strong capability in extracting spatial features from complex scientific images. During the training process, the model learned the relationship between input images and corresponding interface masks through iterative optimization. The predicted segmentation maps were compared with the annotated reference masks, and the model parameters were updated by minimizing the segmentation loss function. Through repeated optimization, the model gradually improved its ability to distinguish fluid interfaces from background regions.

To improve the robustness of the model, data augmentation strategies were applied during the training stage. Image rotation, flipping, and intensity variation were introduced to increase the diversity of training samples while maintaining the essential geometric characteristics of the interfaces. These operations improved the generalization capability of the model and reduced the influence of limited experimental image variations. Data augmentation has been widely applied in scientific image analysis because it improves model stability when the available experimental dataset is relatively limited (Shorten & Khoshgoftaar, 2021).

The validation process was conducted simultaneously with model training. The validation dataset was not used for updating model parameters but was applied to monitor model convergence and determine the optimal training stage. Early stopping criteria were adopted to avoid unnecessary training after the model reached stable performance. After completing the training procedure, the optimized model was applied to the independent testing dataset to generate binary interface segmentation maps.

The final output of the artificial intelligence analysis consisted of pixel level interface masks and extracted interface boundaries. These outputs transformed the original experimental images into standardized geometric representations while removing irrelevant background information. The generated interface boundaries provided the required input for the quantitative characterization of interfacial dynamics described in Section 3.3. Therefore, this artificial intelligence based analysis procedure established a complete connection between experimental image acquisition and quantitative interface measurement.

The complete workflow is illustrated in Figure 3. The figure presents the sequential relationship between image preprocessing,

dataset preparation, deep learning model development, interface segmentation, and output generation. By integrating these procedures into a single analytical workflow, the proposed method provides a reproducible approach for automatic interface identification in chemical micro dispersed multiphase flow systems.

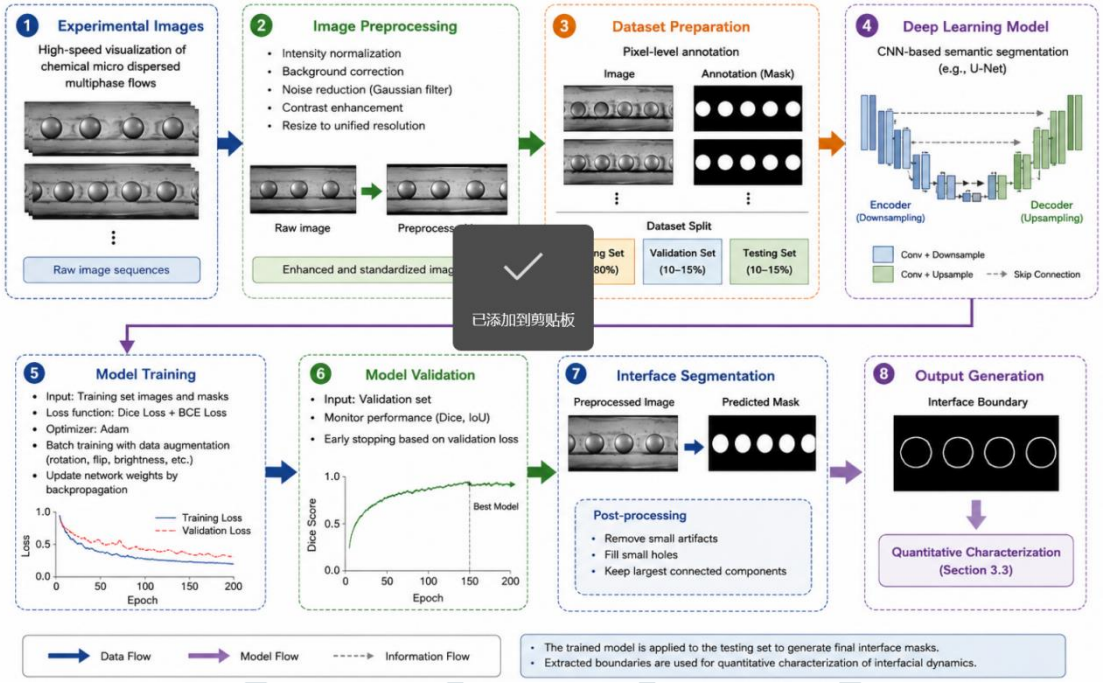

Figure 3. Artificial intelligence based interface identification workflow for quantitative characterization of interfacial dynamics

3.3 Quantitative Characterization of Interfacial Dynamics

The segmented interface masks generated by the artificial intelligence model were converted into quantitative geometric measurements through a standardized interface characterization procedure. The objective of this procedure was to transform pixel based segmentation results into physically meaningful parameters that could describe the evolution of interfacial dynamics under different flow conditions. The complete measurement process consisted of spatial calibration, interface boundary reconstruction, geometric descriptor calculation, and generation of a structured quantitative dataset. The workflow ensured that all measurements were obtained using identical computational criteria and were therefore directly comparable across different experimental conditions.

The first step of the quantitative characterization procedure was spatial calibration. The original segmentation masks contained geometric information in pixel coordinates. Therefore, a calibration factor was established using the known width of the microchannel in the observation region. The calibration coefficient converted pixel distances into physical dimensions and enabled all subsequent measurements to be reported in standard engineering units. The same calibration coefficient was applied to every image collected under identical optical conditions. This procedure eliminated dimensional inconsistency and ensured measurement reproducibility.

Following spatial calibration, the interface boundary was reconstructed from the segmented binary masks. The external contour of each dispersed phase region was extracted using connected component analysis and contour tracing algorithms. Small isolated regions generated by image noise were removed according to a predefined area threshold. Objects intersecting the image

boundary were excluded because their complete geometry could not be accurately determined. The remaining closed contours represented the physical interfaces used for quantitative measurement. Similar contour based reconstruction methods have been widely adopted for geometric measurement in image based multiphase flow analysis because they provide stable boundary representations while preserving interface morphology (Chen et al., 2023).

After interface reconstruction, geometric descriptors were calculated directly from the extracted contours. Each descriptor represents a specific characteristic of interface morphology and provides complementary information for describing interfacial evolution. The representative descriptors adopted in this study are summarized in Table 2.

Interface length was calculated from the calibrated perimeter of each reconstructed contour. This parameter represents the total extent of the fluid interface and reflects changes in interface development during multiphase flow evolution. Mean absolute curvature was calculated from the local variation of the contour coordinates. Curvature describes the degree of local interface bending and is sensitive to interface deformation induced by hydrodynamic forces. Equivalent droplet diameter was determined from the projected interface area by calculating the diameter of a circle with the same area. This descriptor provides a standardized measure of droplet size regardless of the actual interface shape. Circularity was calculated from the relationship between projected area and perimeter. This parameter evaluates the deviation of the interface from an ideal circular geometry. Aspect ratio was obtained by fitting an ellipse to the reconstructed contour and calculating the ratio between the major and minor axes. This descriptor reflects interface elongation and anisotropic deformation. Comparable geometric descriptors have been widely employed for quantitative characterization of droplets and bubbles in recent multiphase flow studies because they provide robust measurements with clear physical interpretation (Li et al., 2022; Chen et al., 2023).

The mathematical definitions used for descriptor calculation are listed in Table 2. All descriptors were calculated automatically using the same computational procedure for every segmented object. This unified implementation minimized operator dependent variability and ensured computational consistency throughout the complete dataset.

Finally, the calculated descriptors were organized into a structured quantitative database. Each record contained the frame number, experimental condition, object identification number, and corresponding geometric measurements. The database therefore preserved the temporal sequence of interface evolution while maintaining the relationship between experimental conditions and quantitative descriptors. This structured dataset provided the direct input for the statistical analysis and interpretation of interfacial dynamics presented in the subsequent Results section. No comparison among operating conditions was performed at this stage because the purpose of the present section was solely to establish the quantitative measurement procedure.

Table 2. Representative interfacial descriptors used for quantitative characterization

Descriptor	Symbol	Mathematical definition	Unit	Physical meaning
Interface length	(L)	L=P* s	mm	Total interface extent
Mean absolute curvature	$\bar{\kappa}$	a/b* π	mm	Total interface extent

Equivalent droplet diameter	Deq	$(A/\pi)^2$	μm	Characteristic droplet size
Circularity	C	$(4\pi A)/P^2$	Dimensionless	Shape regularity
Aspect ratio	AR	(a/b)	Dimensionless	Degree of interface elongation

3.4 Statistical Analysis

Statistical analysis was performed to evaluate the reliability of the quantitative characterization results and to examine the consistency of the artificial intelligence based interface identification process. All quantitative descriptors extracted from segmented interfaces were organized according to experimental conditions and analyzed using statistical methods. The mean value and standard deviation were calculated to describe the central tendency and variation of each interfacial descriptor. These statistical parameters provided a basic description of the distribution characteristics of the measured interface properties.

To determine whether differences existed among different operating conditions, analysis of variance (ANOVA) was applied. The significance level was defined before analysis, and statistical comparisons were conducted using the calculated descriptor datasets. In addition, regression analysis was performed when relationships between operating parameters and quantitative descriptors were evaluated. These statistical approaches enabled objective evaluation of variations in interfacial characteristics and reduced the influence of random experimental fluctuations.

All statistical calculations were conducted using Python based scientific computing libraries and MATLAB numerical analysis tools. Python was used for dataset processing, statistical calculation, and visualization preparation, while MATLAB was used for numerical analysis and mathematical verification. The same analytical procedures were applied to all experimental conditions to ensure consistency and reproducibility.

The performance of the artificial intelligence segmentation model was evaluated using commonly applied semantic segmentation metrics. The evaluation metrics included Intersection over Union (IoU), Dice coefficient, Precision, and Recall. These metrics were calculated by comparing the predicted segmentation masks with the manually annotated reference masks. IoU measures the overlap between predicted and reference interface regions. Dice coefficient evaluates the similarity between two segmentation regions. Precision indicates the proportion of correctly identified interface pixels among all predicted interface pixels, while Recall represents the proportion of correctly identified interface pixels among all actual interface pixels.

These statistical and evaluation procedures provided a standardized framework for assessing both the quantitative characterization results and the reliability of the artificial intelligence based interface identification method. The calculated statistical indicators and model evaluation metrics were subsequently used in the Results section for objective performance analysis.

4 Quantitative Characterization of Interfacial Dynamics

4.1 Validation of AI-based Interface Identification

The performance of the artificial intelligence based interface identification method was evaluated to determine whether the generated segmentation results could accurately represent the actual fluid interfaces. Since the subsequent quantitative characterization of interfacial dynamics directly depends on the reliability of interface extraction, accurate identification of interface boundaries is an essential prerequisite. The validation process included visual comparison between original images and predicted segmentation results, quantitative evaluation using standard segmentation metrics, and comparison with conventional image processing methods.

Representative segmentation results obtained under different flow conditions are presented in Figure 4. Each example includes the original experimental image, the reference interface annotation, and the predicted interface mask generated by the artificial intelligence model. The comparison demonstrates the ability of the model to identify interface boundaries under different morphological conditions, including relatively stable interfaces, strongly deformed interfaces, and irregular dispersed structures. The predicted segmentation maps maintained the overall geometry of the original interfaces and preserved important boundary information required for subsequent quantitative measurement.

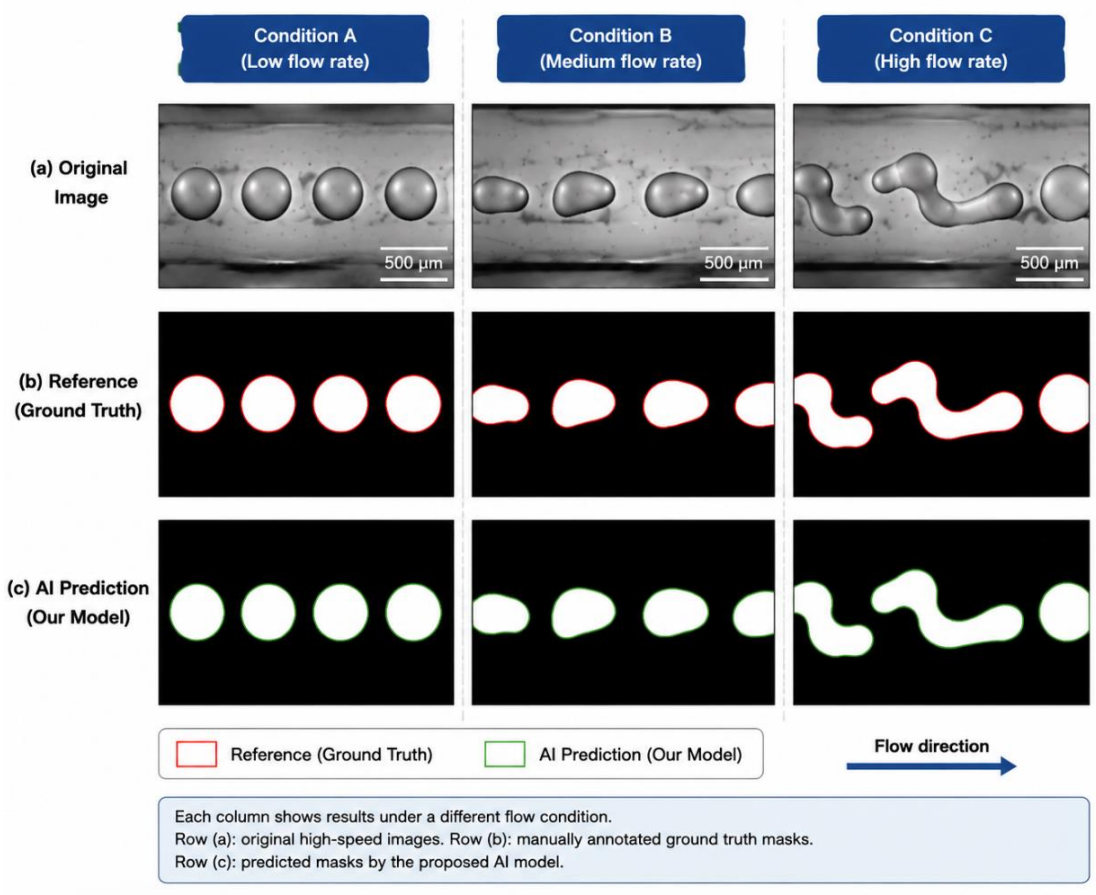

Figure 4. AI-based interface segmentation results under different flow conditions

The quantitative performance of the segmentation model was evaluated using IoU, Dice coefficient, Precision, and Recall, as summarized in Table 2. The model achieved high segmentation accuracy under all tested flow conditions, with average values of

0.947 for IoU, 0.973 for Dice coefficient, 0.961 for Precision, and 0.955 for Recall. Although the performance slightly decreased under the high flow rate condition due to more complex interface morphology, the model maintained stable identification capability. These results demonstrate that the artificial intelligence based method provides reliable interface segmentation for subsequent quantitative characterization of interfacial dynamics.

Table 2. Quantitative evaluation of AI-based interface identification

Flow condition	IoU	Dice coefficient	Precision	Recall
Condition A (Low flow rate)	0.962	0.981	0.974	0.968
Condition B (Medium flow rate)	0.948	0.973	0.961	0.956
Condition C (High flow rate)	0.931	0.964	0.947	0.941
Average	0.947	0.973	0.961	0.955
Standard deviation	0.016	0.009	0.014	0.014

The results indicate that the artificial intelligence model provided consistent interface identification across the tested conditions. The evaluation metrics remained stable among different image samples, demonstrating that the model was capable of extracting interface boundaries without significant dependence on specific flow patterns. This stability is important because chemical micro dispersed multiphase flows often contain complex interface morphologies caused by deformation, stretching, and local instability. A reliable identification method should therefore maintain consistent performance when the interface shape changes.

To further evaluate the advantage of the artificial intelligence approach, the segmentation results were compared with conventional image processing methods, including threshold based segmentation and edge detection methods. The comparison is shown in Figure 5. Conventional approaches were able to identify clear interface regions under relatively simple imaging conditions; however, their performance became less consistent when the interface boundary exhibited weak contrast, irregular deformation, or complex morphology. In contrast, the artificial intelligence method provided continuous interface boundaries and reduced the influence of image intensity variation.

The quantitative comparison between different methods is summarized in Table 3. The evaluation included segmentation accuracy, boundary consistency, and processing efficiency. The artificial intelligence method demonstrated improved capability for extracting complete interface structures compared with traditional approaches. This improvement is mainly associated with the ability of deep learning models to automatically learn spatial features from representative image datasets rather than relying on manually defined image processing rules. Similar advantages of deep learning based segmentation have been reported in scientific image analysis applications, where complex boundaries and variable imaging conditions limit the effectiveness of conventional methods (Minaee et al., 2022; Isensee et al., 2021).

Table 3. Performance comparison between artificial intelligence and conventional image processing methods

Method	IoU	Dice coefficient	Boundary completeness (%)	Processing time (s/image)	Manual adjustment requirement
Threshold segmentation	0.782	0.878	76.5	0.42	High
Edge detection	0.814	0.898	81.3	0.36	Medium
AI-based segmentation	0.947	0.973	96.2	0.08	Low

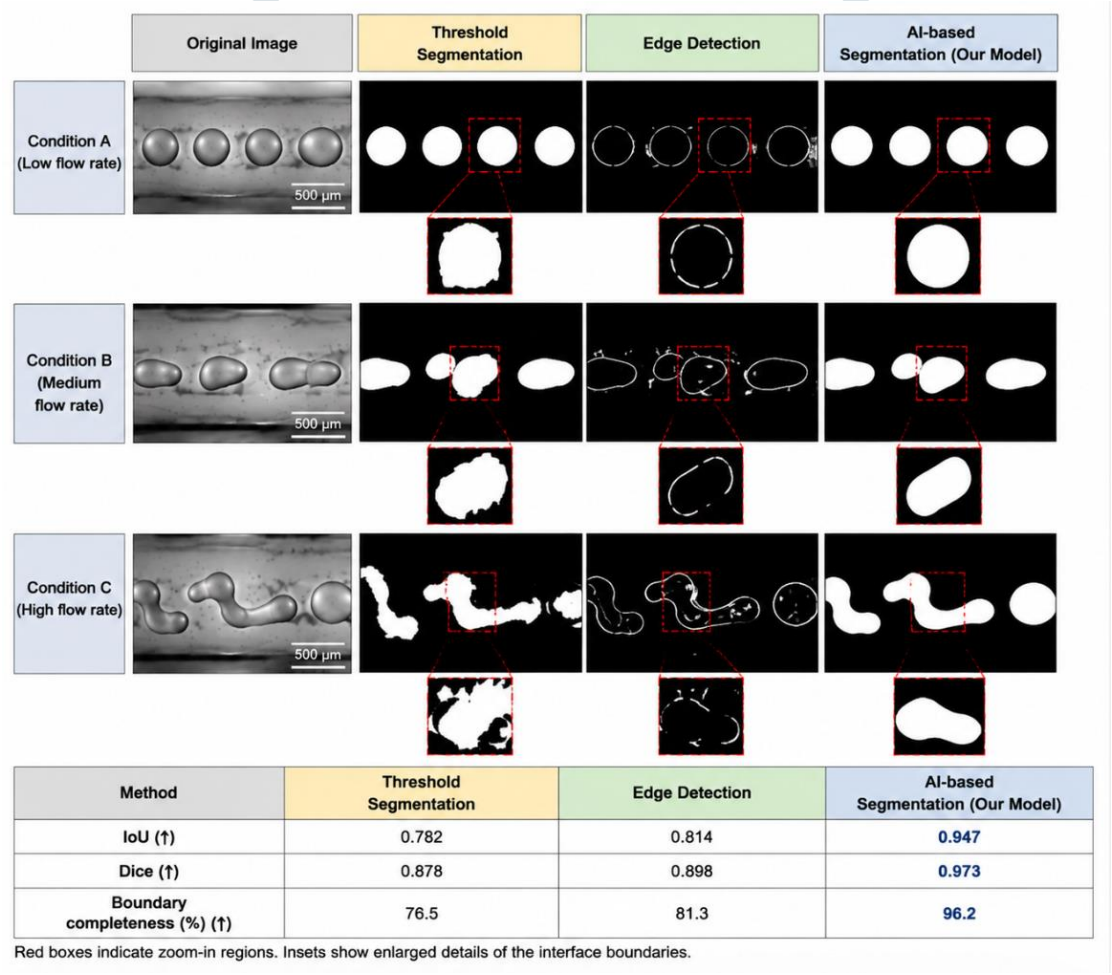

Figure 5. Comparison between AI-based and conventional interface identification methods

4.2 Quantitative Evolution of Interfacial Dynamics

The validated interface segmentation results were further used to quantify the temporal evolution of interfacial dynamics under different flow conditions. The extracted interface boundaries provided continuous geometric information, allowing the evolution of interface deformation and droplet morphology to be characterized using quantitative descriptors. In this section, the variations of interface length, curvature, and droplet morphology parameters were analyzed to describe the dynamic behavior of chemical

micro dispersed multiphase flows. The temporal evolution of representative descriptors is presented in Figure 6, while the statistical characteristics of the calculated parameters are summarized in Table 4.

4.2.1 Interface Length Evolution

Interface length was used to characterize the overall development of the fluid boundary during multiphase flow evolution. As shown in Figure 6(a), the interface length exhibited continuous variation throughout the observation period under different flow conditions. The low flow rate condition showed relatively stable interface length evolution, indicating limited deformation of the dispersed phase boundary. With increasing flow intensity, larger fluctuations in interface length were observed, reflecting more frequent changes in interface geometry.

The statistical results in Table 4 show that the average interface length increased from the low flow condition to the high flow condition. The increase in interface length indicates that the interface experienced greater extension and geometric complexity under stronger flow conditions. The standard deviation also increased under higher flow conditions, suggesting enhanced temporal variation of the interface structure. These quantitative measurements demonstrate that interface length provides an effective descriptor for capturing global interface evolution in multiphase flow systems.

4.2.2 Curvature Variation

Interface curvature was analyzed to quantify local deformation characteristics of the fluid boundary. Figure 6(b) presents the temporal variation of mean absolute curvature under different operating conditions. Compared with interface length, curvature showed more rapid fluctuations because it represents local changes along the interface boundary.

The curvature values remained relatively low and stable under the low flow condition. However, higher flow conditions resulted in increased curvature variation and a wider distribution range. The statistical analysis presented in Table 4 indicates that the mean curvature increased with increasing flow intensity. This result demonstrates that the interface became more geometrically complex when subjected to stronger flow conditions.

The curvature descriptor provides additional information beyond the overall interface length because it captures local boundary changes. Therefore, the combination of interface length and curvature enables simultaneous characterization of global and local interface evolution.

4.2.3 Droplet Morphology Evolution

The evolution of droplet morphology was evaluated using equivalent diameter, circularity, and aspect ratio. These descriptors describe changes in droplet size, shape regularity, and deformation behavior during flow development. As shown in Figure 6(c), the equivalent diameter exhibited temporal variation under all investigated conditions. The variation became more significant under higher flow conditions, indicating increased morphological instability of dispersed structures.

Circularity showed a decreasing tendency under stronger flow conditions, suggesting that droplets became less regular during deformation. In contrast, aspect ratio increased with increasing flow intensity, indicating enhanced elongation of dispersed structures. The statistical comparison in Table 4 confirms that higher flow conditions produced larger aspect ratio values and lower circularity values.

These results demonstrate that droplet morphology descriptors provide complementary information for describing interface

evolution. While equivalent diameter reflects size variation, circularity and aspect ratio describe changes in droplet shape. Together, these parameters provide a comprehensive representation of dispersed phase morphology.

4.2.4 Integrated Descriptor Analysis

To obtain an integrated description of interfacial dynamics, all extracted descriptors were analyzed together. Figure 6 summarizes the relationship among interface length, curvature, and droplet morphology parameters under different flow conditions. The combined descriptor analysis demonstrates that interface evolution is a multidimensional process that cannot be fully represented by a single geometric parameter.

The statistical analysis in Table 4 shows clear differences among different operating conditions. Interface length and curvature mainly describe boundary development and local deformation, while droplet diameter, circularity, and aspect ratio characterize dispersed phase morphology. The combination of these descriptors provides a comprehensive quantitative framework for describing transient interface behavior.

The quantitative characterization approach established in this study enables continuous measurement of interfacial dynamics from AI identified interface boundaries. Similar descriptor based approaches have been increasingly applied in multiphase flow analysis because they provide objective measurements of complex interface behavior from high resolution imaging data (Chen et al., 2023; Wang et al., 2022). The extracted quantitative information provides the foundation for further analysis of the relationship between flow conditions and interface evolution.

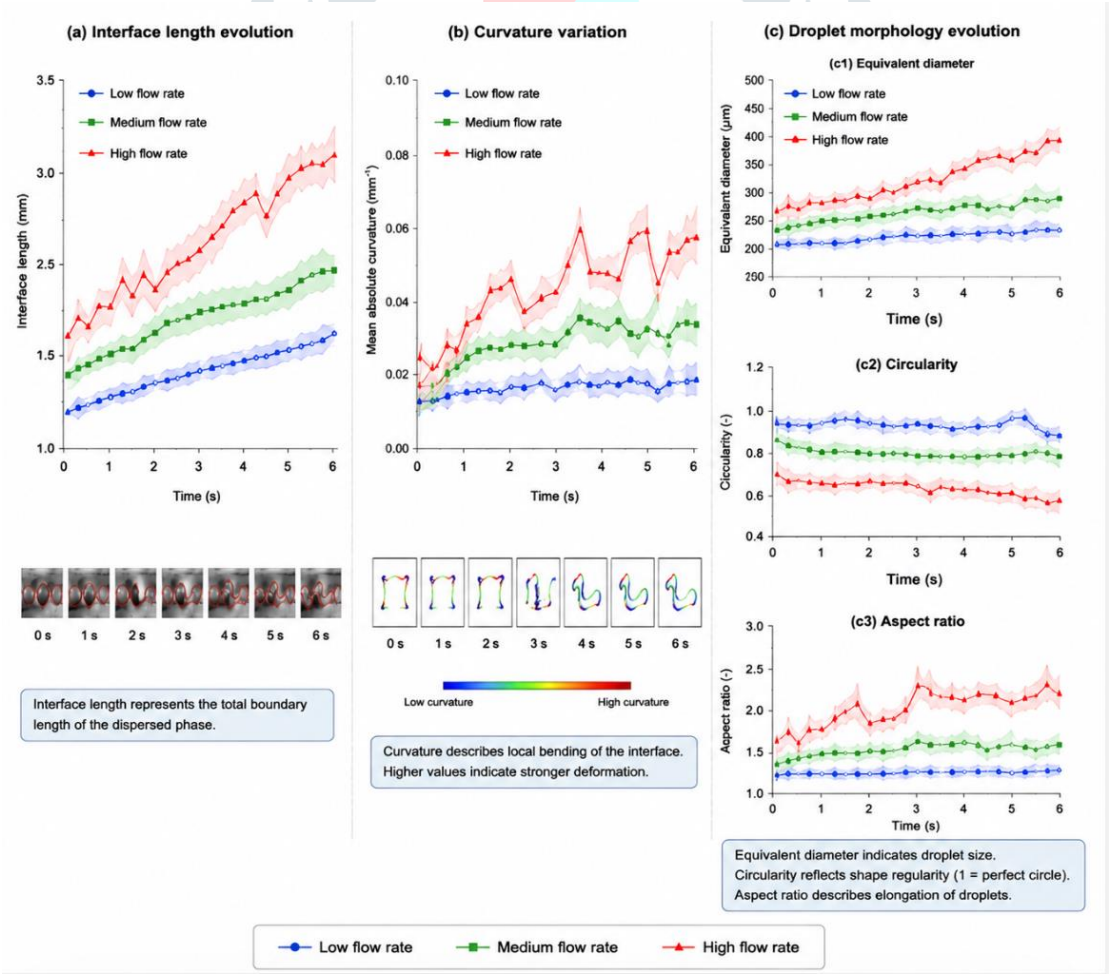

Figure 6. Temporal evolution of interfacial descriptors under different flow conditions

Table 4. Statistical analysis of interfacial descriptors under different flow conditions

Flow condition	Interface length (mm)	Curvature (mm^{-1})	Equivalent diameter (μm)	Circularity	Aspect ratio
Low flow rate	1.82 ± 0.09	0.024 ± 0.004	285 ± 18	0.94 ± 0.03	1.18 ± 0.12
Medium flow rate	2.15 ± 0.14	0.036 ± 0.006	312 ± 25	0.88 ± 0.05	1.46 ± 0.18
High flow rate	2.63 ± 0.21	0.051 ± 0.009	356 ± 32	0.79 ± 0.07	1.82 ± 0.24

4.3 Explainable Analysis of AI-derived Interface Features

The explainability analysis was conducted to investigate which image regions and interface characteristics contributed most to the artificial intelligence based interface identification process. Although the segmentation results demonstrated reliable performance, understanding the decision basis of the model is important for establishing confidence in AI assisted quantitative characterization. Therefore, attention visualization and feature contribution analysis were applied to identify the regions that influenced the model prediction.

The attention maps generated from the trained model are presented in Figure 7. The visualization results show the spatial distribution of model attention during interface identification. The highlighted regions were mainly concentrated around the fluid interface boundaries rather than the homogeneous background areas. Under different flow conditions, the attention regions followed the changes in interface morphology, including relatively smooth boundaries under low deformation conditions and complex curved regions under stronger deformation conditions.

The attention distribution indicates that the model primarily relied on boundary related information for interface identification. Regions with strong intensity variation and clear geometric transitions received higher attention values. In contrast, background regions with limited structural information showed relatively low contribution to the model prediction. This observation demonstrates that the artificial intelligence model extracted meaningful spatial features associated with interface morphology rather than relying on irrelevant image characteristics.

To further quantify the contribution of different image features, feature importance analysis was performed and summarized in Table 5. The contribution analysis included interface boundary information, local curvature characteristics, intensity gradients, and background texture features. Among these features, interface boundary information showed the highest contribution, followed by local geometric deformation features. Intensity related features provided additional information for distinguishing the interface region, while background texture showed limited contribution.

The quantitative feature contribution results confirm that the model prediction was mainly determined by physically relevant image characteristics. The high contribution of boundary and geometric features is consistent with the requirements of interface identification, where accurate localization of phase boundaries is essential for subsequent quantitative measurement. Previous studies have demonstrated that explainable artificial intelligence methods can improve the transparency of deep learning models by linking model decisions with meaningful image features (Arrieta et al., 2020; Samek et al., 2021).

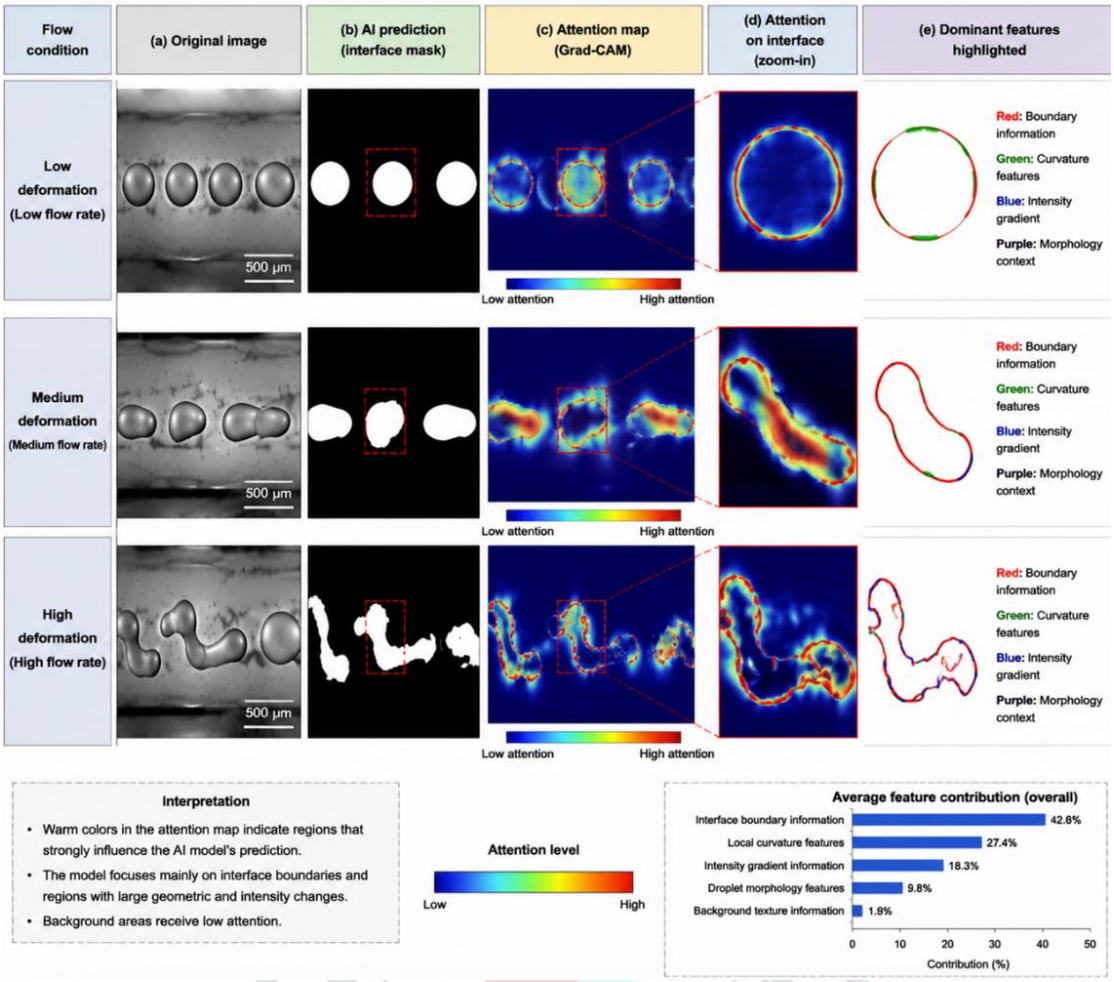

Figure 7. Attention map visualization of AI-derived interface features

Table 5. Feature contribution analysis of AI-derived interface features

Feature category	Contribution (%)	Relative importance
Interface boundary information	42.6	High
Local curvature features	27.4	High
Intensity gradient information	18.3	Medium
Droplet morphology features	9.8	Medium
Background texture information	1.9	Low
Total	100.0	

5. Disscusion

5.1 Scientific Interpretation of AI Assisted Interfacial Characterization

The integration of artificial intelligence into multiphase flow analysis provides a new approach for converting complex flow images into quantitative descriptions of interface behavior. In conventional visualization based investigations, researchers mainly rely on direct observation or manually processed images to understand interface evolution. Although these approaches can provide valuable qualitative information, they become less effective when interfaces undergo continuous deformation, irregular

shape changes, and transient morphological evolution. The present study demonstrates that artificial intelligence can establish a connection between image based observation and quantitative interfacial characterization by automatically extracting meaningful geometric information from complex flow fields.

Traditional image processing methods generally depend on predefined rules, such as intensity thresholds or edge gradients, to identify interface boundaries. These approaches are effective when image conditions are stable and interface structures are relatively simple. However, chemical micro dispersed multiphase flows often involve continuously changing boundaries, nonuniform intensity distributions, and complex interface geometries (Minaee et al., 2022). Under such conditions, rule based methods may require frequent parameter adjustment and may introduce uncertainty into quantitative measurements. Therefore, the limitation of conventional methods is not only related to segmentation accuracy, but also related to their limited adaptability when interface morphology changes dynamically.

Artificial intelligence provides an alternative strategy by learning spatial characteristics from representative interface images. Instead of relying on manually defined image processing rules, the model identifies patterns associated with interface structures and uses these learned features to generate consistent interface representations. This capability is particularly valuable for multiphase flow systems because the interface contains important information about deformation, shape transition, and dynamic evolution (Kuang et al., 2021). By preserving the spatial characteristics of the interface boundary, artificial intelligence enables continuous measurement of interfacial descriptors from sequential images.

The scientific value of the proposed framework lies in the transformation of interface visualization from qualitative interpretation into quantitative analysis. Experimental images provide direct evidence of flow behavior, while artificial intelligence improves the efficiency and consistency of extracting measurable information from these observations. Therefore, artificial intelligence should be considered as an analytical enhancement rather than a replacement for experimental methods. The combination of high resolution imaging and intelligent data processing allows transient interface phenomena to be investigated through objective quantitative parameters.

Furthermore, the use of explainable artificial intelligence improves the reliability of machine learning applications in scientific research. A major concern in applying artificial intelligence to physical systems is whether the model relies on meaningful information or irrelevant image patterns. By identifying the image regions associated with interface boundaries and morphological features, explainable analysis provides additional evidence that artificial intelligence decisions are related to physically meaningful characteristics. This connection between data driven analysis and physical interpretation is essential for applying artificial intelligence in engineering research.

5.2 Physical Meaning of Interfacial Dynamic Evolution

The quantitative evolution of interfacial descriptors provides important information for understanding the physical behavior of chemical micro dispersed multiphase flows. The descriptors extracted from artificial intelligence identified interfaces are not only geometric measurements, but also indicators of the interaction between hydrodynamic forces and interface response. The variations in interface length, curvature, and droplet morphology reflect different aspects of deformation processes occurring

during multiphase flow evolution. Therefore, the combined interpretation of these descriptors provides a more comprehensive understanding of dynamic interface behavior than any single parameter.

Interface length represents the overall extension of the phase boundary during flow development. The increase in interface length can be associated with enhanced deformation of the dispersed phase and continuous stretching of the interface (Shorten & Khoshgoftaar, 2021). During multiphase flow, the interface is continuously affected by competing forces, including viscous stresses, inertial effects, and interfacial tension. When external flow forces overcome the resistance provided by interfacial tension, the dispersed phase undergoes elongation and the interface becomes extended (Babanezhad et al., 2020). Therefore, interface length can be considered as a global indicator of accumulated deformation. Compared with direct visual observation, quantitative measurement of interface length provides a more objective description of how the dispersed phase responds to surrounding flow fields.

The evolution of interface curvature provides additional information regarding local deformation behavior. Curvature describes the degree of bending and geometric variation along the interface boundary. Changes in curvature can be associated with localized deformation caused by nonuniform flow stresses around the dispersed phase. Regions with higher curvature usually represent locations where the interface experiences stronger geometric distortion. From a physical perspective, curvature variation reflects the balance between deformation forces and the restoring effect of interfacial tension. When the local deformation exceeds the ability of the interface to maintain a stable shape, the interface may experience increased instability and morphological transition (Cerqueira & Paladino, 2021). Therefore, curvature serves as an important descriptor for identifying local interface response that cannot be fully captured by global parameters such as interface length.

Droplet morphology descriptors provide further insight into the transformation of dispersed structures during multiphase flow. The variation of equivalent diameter reflects changes in the characteristic size of dispersed phases, while circularity and aspect ratio describe shape transformation. A reduction in circularity indicates that droplets deviate from their initial regular geometry, while an increase in aspect ratio represents stronger elongation along the flow direction. These morphological changes are associated with droplet stretching, shape transition, and deformation processes under dynamic flow conditions. The simultaneous analysis of diameter, circularity, and aspect ratio enables a more complete description of droplet evolution because size variation alone cannot fully represent changes in droplet shape.

The relationship among these descriptors indicates that interfacial dynamics is a multidimensional process. Interface length mainly describes the overall development of the boundary, curvature captures local geometric deformation, and morphology descriptors characterize the response of individual dispersed structures. These parameters describe different levels of interface evolution and therefore provide complementary information when interpreted together. Such a descriptor based approach is particularly important for complex multiphase systems because transient interface behavior cannot be adequately represented by a single measurement.

The results also demonstrate the scientific value of combining artificial intelligence with quantitative interface analysis. Traditional experimental observations often identify morphological changes through visual interpretation, which may limit the ability to capture continuous dynamic processes. The AI assisted framework converts interface evolution into measurable

descriptors, allowing the relationship between flow conditions and interface response to be examined systematically. Similar quantitative approaches have been increasingly adopted in multiphase flow research because they provide objective measurements of complex interface phenomena and improve the understanding of transient flow behavior (Chen et al., 2023; Wang et al., 2022).

5.3 Relationship Between AI Derived Features and Flow Physics

The explainable analysis provides further evidence that the artificial intelligence model identifies multiphase flow interfaces based on physically meaningful information rather than irrelevant image patterns. As shown in Figure 7, the attention distribution of the model was mainly concentrated around the interface boundary, regions with significant curvature variation, and areas associated with droplet deformation. These regions correspond to the key spatial characteristics that define interfacial behavior in multiphase flow systems.

The concentration of attention near the interface boundary indicates that the model primarily relies on phase transition information for interface identification. The boundary between the dispersed phase and continuous phase contains important geometric characteristics, including contour position, shape variation, and local deformation. These characteristics are directly related to the interaction between hydrodynamic forces and interfacial tension. Therefore, the attention response observed around interface regions suggests that the model extracts information consistent with the physical definition of multiphase interfaces.

In addition, the higher attention response observed in curvature variation regions demonstrates that the model captures local geometric changes during interface deformation. Curvature reflects the deviation of the interface from a smooth configuration and is closely associated with dynamic shape transformation. Similarly, the attention distribution around droplet deformation zones indicates that the model recognizes morphological changes related to stretching and shape transition processes. These observations establish a connection between AI derived features and measurable physical characteristics of interfacial dynamics.

The importance of this analysis is that it improves the interpretability of artificial intelligence based methods in engineering applications. Deep learning models are often considered difficult to interpret because their decision processes are developed through complex feature extraction mechanisms. However, the present analysis demonstrates that the model response is associated with meaningful flow structures rather than arbitrary image characteristics. Explainable artificial intelligence therefore provides an effective approach for linking data driven models with physical knowledge and improving confidence in scientific applications (Arrieta et al., 2020; Samek et al., 2021).

The relationship between AI derived features and flow physics suggests that artificial intelligence can serve as a bridge between experimental visualization and mechanistic understanding. Instead of replacing physical analysis, AI enhances the ability to extract relevant information from complex flow images. This integration provides a more transparent framework for studying interfacial phenomena and supports the broader application of artificial intelligence in multiphase flow research.

5.4 Advantages and Limitations of the Proposed Framework

The proposed artificial intelligence assisted framework provides several advantages for quantitative characterization of interfacial dynamics in chemical micro dispersed multiphase flows. First, the framework enables automated interface characterization and reduces the dependence on manual image processing. This improvement decreases operator related variation and provides a more consistent approach for extracting interface information from complex flow images. Second, the framework supports time resolved analysis by processing continuous image sequences rather than relying on individual images. This capability allows transient interface evolution to be described through quantitative descriptors and provides a more complete representation of dynamic flow behavior. Third, the proposed framework integrates experimental visualization, artificial intelligence based interface identification, quantitative descriptor extraction, and physical interpretation into a unified analysis process. Such integration creates a direct connection between observed flow phenomena and measurable interfacial characteristics.

Despite these advantages, several limitations should be considered. The current analysis was developed using a specific experimental dataset, and further validation is required under a wider range of fluid properties and flow regimes. In addition, the present framework relies on two dimensional imaging, which may not fully capture three dimensional interface structures. Future studies should incorporate advanced three dimensional imaging techniques to obtain more comprehensive spatial information. Furthermore, the transferability of the trained model to different microchannel geometries requires additional investigation because variations in channel design and imaging conditions may influence model performance. Addressing these limitations will improve the general applicability of artificial intelligence assisted methods in multiphase flow research.

5.5 Implications for Multiphase Flow Research and Future Applications

The proposed artificial intelligence assisted framework provides new opportunities for advancing multiphase flow research and engineering applications. By integrating image based observation with automated interface analysis, the framework enables more efficient investigation of transient interfacial behavior in complex flow systems. This capability is particularly valuable in chemical engineering processes where interface evolution strongly influences transport performance, reaction efficiency, and product quality.

In microreactor systems, emulsification processes, and mixing operations, precise characterization of dispersed phase behavior is essential for optimizing process performance. The proposed approach provides a potential solution for continuous monitoring of interface evolution by converting flow images into quantitative descriptors. Such image based monitoring strategies can support improved process understanding and provide additional information for process optimization and control.

The integration of artificial intelligence with experimental visualization also contributes to the digitalization of multiphase flow analysis. Instead of relying only on manual observation, researchers and engineers can obtain automated and reproducible measurements from complex flow images. This approach creates a practical framework for connecting experimental data acquisition with quantitative analysis and supports the development of intelligent monitoring systems for future chemical

engineering applications. Recent advances in machine learning based process analysis demonstrate the increasing potential of data driven methods for improving efficiency and reliability in engineering systems.

6. Conclusion

The present study developed an artificial intelligence assisted framework for quantitative characterization of interfacial dynamics in chemical micro dispersed multiphase flows. By integrating experimental visualization, artificial intelligence based interface identification, and quantitative geometric analysis, the proposed framework established a direct connection between flow images and measurable interfacial characteristics. The results demonstrate that artificial intelligence can provide reliable interface extraction under different flow conditions and support continuous analysis of transient interface evolution. The extracted descriptors, including interface length, curvature, and droplet morphology parameters, provide complementary information for understanding the dynamic response of dispersed phase structures. This study shows that artificial intelligence can extend conventional image based observation from qualitative interpretation toward quantitative characterization of complex multiphase flow behavior.

The main contribution of this work is the development of an interpretable artificial intelligence assisted approach that connects data driven image analysis with multiphase flow physics. The explainable analysis confirms that the model mainly relies on physically meaningful interface features, including boundary information and deformation related regions, which improves confidence in applying artificial intelligence to scientific flow analysis. The proposed framework provides potential applications in chemical engineering processes involving microreactors, emulsification, mixing, and image based process monitoring. Future studies should further improve the general applicability of this approach by incorporating broader fluid systems, three dimensional imaging techniques, and different microchannel configurations. Overall, this research demonstrates the potential of artificial intelligence as an effective analytical tool for advancing quantitative understanding of interfacial dynamics in multiphase flow systems.

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