Nuclear Engineering and Technology 54 (2022) 4751–4758

Contents lists available at ScienceDirect

Nuclear Engineering and Technology

journal homepage: www.elsevier.com/locate/net

Original Article

Two-phase flow pattern online monitoring system based on convolutional neural network and transfer learning

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ARTICLE INFO

Article history:
Received 8 January 2022
Received in revised form
21 July 2022
Accepted 23 July 2022
Available online 9 August 2022

Keywords:
Flow pattern
Online monitoring system
Artificial neural network (ANN)
Convolutional neural network (CNN)
Transfer learning
ResNet50

ABSTRACT

Two-phase flow may almost exist in every branch of the energy industry. For the corresponding engineering design, it is very essential and crucial to monitor flow patterns and their transitions accurately. With the high-speed development and success of deep learning based on convolutional neural network (CNN), the study of flow pattern identification recently almost focused on this methodology. Additionally, the photographing technique has attractive implementation features as well, since it is normally considerably less expensive than other techniques. The development of such a two-phase flow pattern online monitoring system is the objective of this work, which seldom studied before. The ongoing preliminary engineering design (including hardware and software) of the system are introduced. The flow pattern identification method based on CNNs and transfer learning was discussed in detail. Several potential CNN candidates such as ALexNet, VggNet16 and ResNets were introduced and compared with each other based on a flow pattern dataset. According to the results, ResNet50 is the most promising CNN network for the system owing to its high precision, fast classification and strong robustness. This work can be a reference for the online monitoring system design in the energy system.

1. Introduction

Two-phase flow may almost exist in every branch of the energy industry, such as conventional petroleum, solar energy, nuclear energy, refrigeration, geothermal energy extraction, offshore wind turbines, and various types of chemical reactors [1,2], which leads to different types of flow patterns (also called flow regimes). The existence of a particular flow pattern depends on a variety of parameters, which include the properties of the fluids, the flow channel size, geometry and orientation, body force field and flow rates, etc., [3]. On the other hand, the accuracy and stability of the online measurement of numerous parameters (e.g., two-phase flow rate), which is essential for the energy industry, depend on the online prediction of flow pattern [4]. It is very essential and crucial to monitor flow patterns and their transitions accurately not only during normal operations (for the purpose of optimizing the overall performance) but also potential abnormal transient (for the purpose of enhancing the safety by fast response) of the energy systems [5,6]. For example, slug flow is very common in offshore gas production and transportation systems; stratified flow is frequently observed in petroleum and natural gas systems [7]. For safety-critical applications such as nuclear energy, one misidentification can lead to an irreparable disaster [8,9]. It was shown in some practical experiments that proposed online monitoring system can improve the effectiveness of energy system, save time in searching abnormal cause and prevent accidents from happening [10].

Nowadays, instrument-based flow pattern identification is of interest in the design, analysis and operation of many two-phase flow systems owing to its higher accuracy. The instrument-based measurement methods can be divided into two types: intrusion and non-intrusion. The intrusive measurement of the flow pattern is a direct measurement, but the probes may impact or change the flow patterns [11]. Commonly, intrusive techniques involve high costs associated with installation and maintenance [12]. Since images of a flow can be produced in transparent pipes easily with visible light, and either X-rays or gamma-rays are applicable in metal pipes [13], a more challenging alternative would be to use these images as non-intrusive methods. Non-intrusive measurements, such as dynamic neutron radiographic images and high-speed camera photos,

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https://doi.org/10.1016/j.net.2022.07.016

constitute easily obtainable global and high qualitative signals of two-phase flow patterns, comparing with those of intrusive measurements, which may exhibit location-dependency and require lengthy capture times. Furthermore, non-intrusive techniques may reduce costs. According to the literature, it is no doubt that non-intrusive measurement is the development direction for flow pattern identification.

But one problem for the non-intrusive techniques is that they may be less accurate compared with intrusive techniques [12] while there is an increasing demand for more accurate two-phase flow pattern identification in the last decades with the development of technology and requirement of the industry. Due to this fact, many investigations on non-intrusive techniques are found in the literature with the aim of improving accuracy [14,15].

The introduction of artificial intelligence and artificial neural network (ANN) into the energy industry was a frontier topic these years, which led to several methodologies based on machine learning adopted to predict flow patterns in the two-phase flow [16,17]. With the high-speed development and success of deep learning based on convolutional neural network (CNN), the study of flow pattern identification in recent five years almost focused on this methodology [18,19].

Furthermore, many researchers have worked on the online recognition of flow patterns [20]. Xie and Ghiaasiaan [21] have proposed on online two-phase flow pattern identification method based on ANN. Xie et al. [22] have introduced a fuzzy recognition method for online flow pattern identification. In the recent years, several online monitoring system of two-phase flow pattern based on deep learning have been developed [23,24]. The most popular deep learning method nowadays is CNN, which has the potential application for flow pattern online monitoring. Although there were several works in the literature that aim to identify the two-phase flow patterns offline using CNN or other methodologies, there is a lack of tools to monitor the flow pattern online during normal operations and abnormal conditions. The limit to this technology is that the training of images for ANN is always time-consuming.

To solve this dilemma, the principal objective of this study focuses on developing a methodology of an online flow pattern monitoring system, which is based on CNN and transfer learning. It is thought that this method responds faster and costs lower than other monitoring system. This system is useful for both the design practitioners and the researchers in energy engineering, and benefits to their collaboration [25]. The proposed framework for developing the online monitoring system includes dataset image library creation, data augmentation, CNN model generation, and performance evaluation, etc. The main contributions of this paper can be summarized as follows:

(1) a draft version of two-phase flow pattern online monitoring system is built based on CNN and the transfer learning. The benefit of this system is high precision, fast classification, strong robustness.
(2) several state-of-the-art CNNs were selected as potential candidates for the system. After a preliminary comparison of them in detail, the ResNet50 network is suggested since it is accurate, robust to noise, and swift.

The rest of this paper is organized as follows. Section 2 will introduce the structure of the flow pattern online monitoring system which is under preliminary design. Section 3 will introduce the machine learning algorithm of the online monitoring system – (1) CNN methodology and the potential CNN candidates, (2) transfer learning. Section 4 will analyze the adaptability of potential CNNs step by step based on a two-phase flow pattern dataset, making our selection – ResNet50 – convincing. Finally, the conclusion of the work is presented in Section 5.

2. Structure of the flow pattern online monitoring system

The flow pattern online monitoring system is under design currently. It could be divided into two parts: the hardware and the software.

2.1. Hardware design

The schematic of the system is shown in Fig. 1. The hardware of the system consists of pipe sections, controllers, light sources, high-speed cameras and computer (with monitor). In Fig. 1, "$1 - N$" means that the online monitoring system has the capability of identifying the flow patterns at several pipe sections simultaneously. The arrows in the figure represent the direction of fluid or data transmission. Actually, this system may be online or offline depending on its application scenarios, its data processing mode and capability. It should be noted that if the application scenario is opaque pipe, instead of camera images, other non-intrusive instrument (e.g., neutron radiography and gamma-rays, etc.) may be used and the method for software may be modified correspondingly.

(1) the fluid information (e.g., the fluid material, the mass flow, pressure and temperature, etc.) at the pipe inlet is controlled and monitored by a "controller". As feedback, the above-mentioned parameters may be adjusted by the controller according to the actual requirement.
(2) a light source is used for a more suitable surrounding environment for photographing, making the images clearer for analysis. Furthermore, the light source may connect with the high-speed camera, and work synchronously with it to enhancing the availability of the images.
(3) the pipe sections are observed using high-speed cameras. To guarantee the suitability and precision of the images during the measurements, the mode, resolution, photo frequency (in frames per second, fps) and position, etc. of the cameras, should be designed and adjusted. The real-time flow pattern image data will be transfer to the computer by the data converters and high-speed cables between the computer and cameras.
(4) the monitoring system is based on software on the computer, which is the most significant part and will be introduced in the following part of this section.

2.2. Software design

The preliminary design of the software interface for the flow

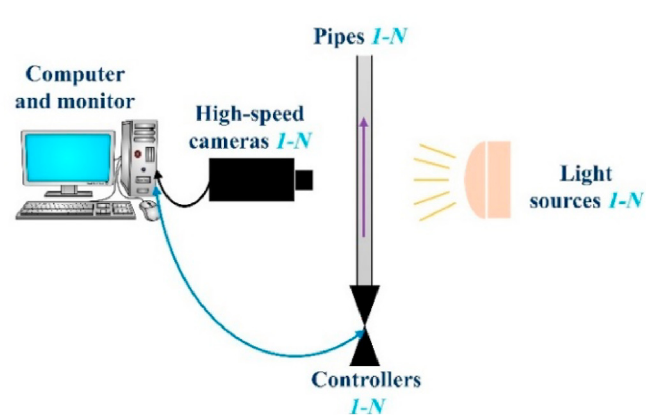

Fig. 1. Schematic of the flow pattern online monitoring system.

pattern online monitoring system is shown in Fig. 2. The interface is divided into two parts: (1) the display area, and (2) the analysis and control area. The display area is used for summarizing the comprehensive information of the pipe sections, the cameras, and most importantly the images, from different sensors/terminals. The real-time image can be chosen and displayed on the screen if it is required by the user. The area for analysis and control has the following four functions:

(1) CNN network selection: for preliminary design, several CNN networks (such as GoogLeNet [26], VggNet [27], ResNet [28], etc.) have been considered as available options for classification.
(2) CNN identification procedure monitor: including the preprocessing of the images, training and testing of the images dataset, and the result plots;
(3) the pipe section and camera parameter control: according to the application conditions of the two-phase flow, the requirements of the pipe section and camera parameters, and the results of CNN classifier, the related parameters may be controlled and adjusted as feedbacks;
(4) as an objective of the proposed system, if some abnormal flow patterns or parameters are detected, the online monitoring system will be responded to by using corresponding function.

The functions 1) and 2) of the analysis and control area are the key algorithms of the system. They directly affect the success of the system as flow pattern classifiers. Therefore, the algorithms and the effectiveness validations will be discussed in the following two sections.

3. Methodology of the flow pattern online monitoring system

The key of the flow pattern online monitoring system is the feature extraction and selection of the real-time flow pattern images. An effective and robust classification method is needed. Currently, CNN becomes dominant in various computer vision tasks and attracted interest across a variety of domains [29,30], such as image classification, speech recognition, behavior recognition, natural language processing, and so on. However, the applications of CNN in the research field of flow pattern identification are very limited, and most importantly, they only considered the offline application. To apply the CNN classifier to identify the online flow patterns, two issues would be overcome: (1) which CNN networks are with high accuracy and efficiency for the application of flow pattern identification? (2) how to make the time-consuming training procedure more effective? To answer these two questions, we would like to introduce our methodology in this section and validate them in section 4.

3.1. The CNN methodology

CNN is a special structure of ANN. Its inputs are two-dimensional images and the features of the images can be automatically obtained by CNN. For detailed knowledge about CNN, any related classic literature or monograph [31,32] could be resorted to. Here only the most important and related information is given. The procedure by using CNN for image classification can be illustrated in Fig. 3 briefly, which can be divided into three steps as follows.

(1) Step 1 (CNN input, blue shading in Fig. 3) prepares the image dataset and its transformed data for CNN calculation. Some specific pretreatments in this step are introduced including image labeling, preprocessing (including image resizing and augmentation) and random division of images into training sets and test sets.
(2) Step 2 (CNN convolution and pooling layers, grey shading in Fig. 3), the image data space is transformed to extracted feature space after the calculations in designated convolution and pooling layers. This step is very crucial for the success of CNN methodology to extract the image features, and different CNNs have different architectures in this part.
(3) Step 3 (CNN fully connected (FC) classification layers), the extracted image features are used to build the FC layers and to get the classification results in image label space based on the classifier. In a CNN, the FC layers can be considered as a

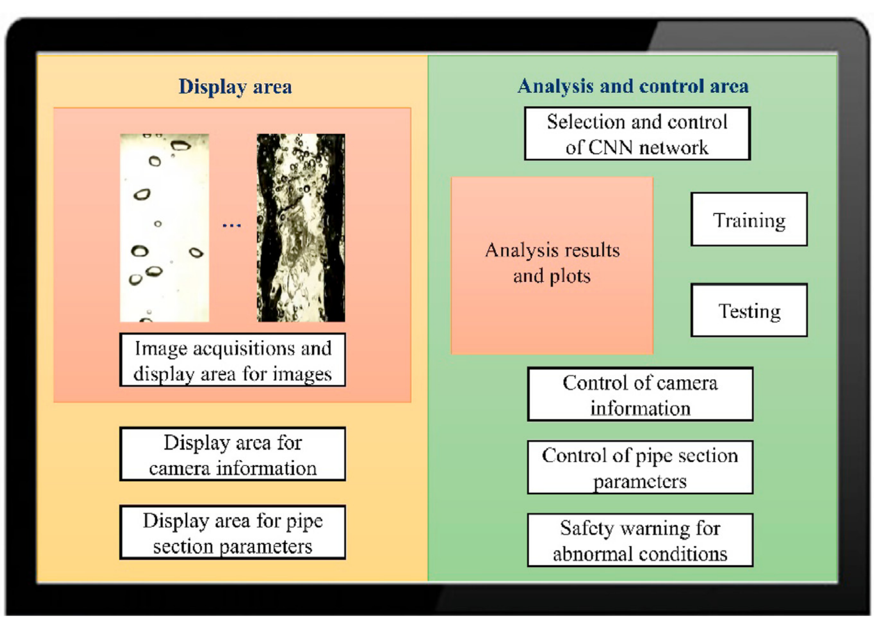

Fig. 2. Software interface design for the flow pattern online monitoring system.

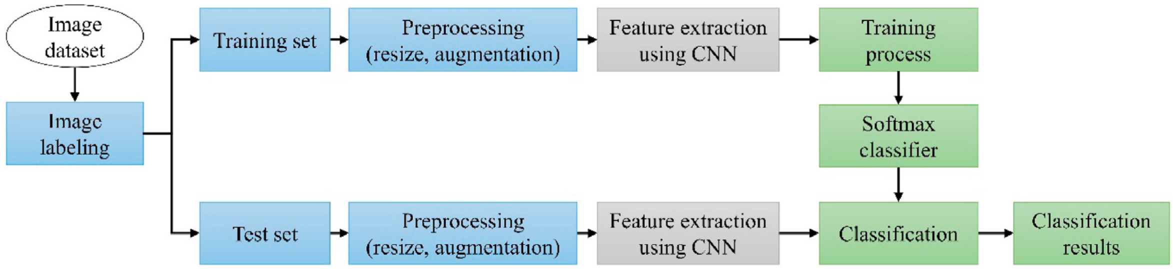

Fig. 3. The procedure by using CNN for image classification.

multilayer perceptron (MLP) [33], and a softmax function is used after the FC layers as a classifier.

Although the general steps of classification are the same for different types of CNNs, their structures are quite different. There is no uniform statement about which type of CNN network is better for application. The following part of this section will introduce some typical CNNs, which may be the potential candidates for the flow pattern online monitoring system.

(1) AlexNet: it includes 5 convolutional layers and 3 FC layers [34]. After each convolutional layer or FC layer, there is a ReLU function $f(x) = max(0,x)$ [35] used the first time to deal with the non-linear part in AlexNet network. Compared with the traditional Sigmoid function, the ReLU function has the advantage of faster training speed and to some extent overcomes the problem of gradient disappearance [36]. Another feature of the AlexNet architecture is the use of a dropout layer behind each FC layer to reduce overfitting [37].
(2) VggNet: this architecture was proposed by the VGG group of Oxford University [28] in 2014. Compared to AlexNet, it replaces the large-size convolution kernel filter by successively using multiple filters of 2×2 and 3×3 convolution kernel sizes. The replacement achieves better results than using larger size convolution kernels and the calculation cost is lower.
(3) GoogLeNet: it is a sparse CNN that only a few neurons in the convolutional layer are effective. Compared to AlexNet, which uses 60 million parameters, GoogLeNet uses only 6.8 million parameters [38]. Moreover, it also uses convolution kernels of different sizes to capture detailed features of different scales $(5 \times 5,\ 3 \times 3,\ 1 \times 1)$. Another important feature of GoogLeNet is that it uses a simple “global average pooling layer” to replace the FC layer at the end of the network [39].
(4) SqueezeNet: it is lightweight CNN developed by UC Berkeley and Stanford University [40]. Its significant advantage is that comparing with other CNN architectures with the same accuracy level, it has a smaller size, which requires much fewer parameters, consequently reducing memory constraints and making it a potential candidate for online monitoring applications. It has already some application of online monitoring system in vehicle community [41].
(5) ResNet: it was developed by He et al. [29] to solve the problem of gradient disappearance effectively since its modification of CNN architecture. It has been used in the online monitoring system of the manufacturing process [42,43]. The key modification to ResNet is to add identity mapping to the network structure. ResNet has several different structures, such as ResNet18, ResNet34, ResNet50, ResNet101 etc. Based on the number of layers in the residual network. In this work, we selected ResNet18 and ResNet50 as potential candidates owing to their good performance in the monitoring systems [44].

As a summary, a comparison of typical potential candidates CNNs for online monitoring system is shown in Table .1. Relatively speaking, ResNet50 is the deepest network with 50 layers; VggNet16 has the most parameters (more than 138 M) and the largest size (528 MB); SqueezeNet has the least parameters and size (less than one-tenth of VggNet16).

3.2. Transfer learning

The time-consuming process of CNN network training could be simplified by the usage of so-called transfer learning. The technique uses the knowledge gained by an already well-trained model using another large-scale dataset (for example, Imagenet [44]). It can be used to solve the dilemma of limit scaled of the dataset and improve accuracy. When transfer learning is applied, the FC layer in the original CNN is removed. Instead, a new FC layer with an output size of four is inserted. Then, a fine-tuning of the modified CNN by training it with flow pattern images from accessible limited dataset. The transfer learning in flow pattern identification is shown in Fig. 4.

As a typical example, a fine-tuning process of AlexNet training is introduced here. Other networks have the same setting and similar fine-tuning training results. We randomly assigned the images of a flow pattern dataset with 70% for training and 30% for test. The options for the AlexNet fine-tuning training were set as shown in Table 2. As an option of optimization, the stochastic gradient descent with momentum (SGDM) optimization [45] was chosen to reduce the training time and the momentum term equaled 0.9. This fine-tuned network was trained for 20 epochs with a learning rate of 0.0001. L2 regularization was used to avert the undesirable overfitting phenomenon. The mini-batch technique [46] was utilized to reduce the requirements for CPU and improve computational efficiency, as it can randomly select a small portion of the training samples in the training set for each iteration process of the model. In this work, the mini-batch size was set at 20.

The features of the flow pattern images were extracted by the AlexNet network from the randomly chosen training dataset. These features were given to the classifier, along with the class labels of training images. The predicted labels for the images were obtained as output from the classifier. Predicted labels are compared with true class labels to evaluate the performance of the classifier. Simultaneously, the test dataset of the flow pattern images was used for the validation of the performance of the AlexNet network and demonstration of its generalization ability. The loss functions and accuracy were monitored during the fine-tuning training process to show the progress and validation results of training over iterations, as shown in Fig. 5. The values in the figure are outputted each three epochs.

According to Fig. 5(a), the loss function values of the training dataset oscillate during the iterations but the amplitudes of the

Table 1
Comparison of typical potential candidates CNNs for online monitoring system.

CNN model	AlexNet	VggNet16	GoogLeNet	SqueezeNet	ResNet18	ResNet50
Year of development	2012	2014	2014	2016	2016	2016
Layers	8	16	19	18	18	50
No. of parameters	59,983,292	138,357,544	6,752,430	1,248,424	11,511,784	25,636,712
Model size (MB)	229	528	49.4	4.4	44.7	98

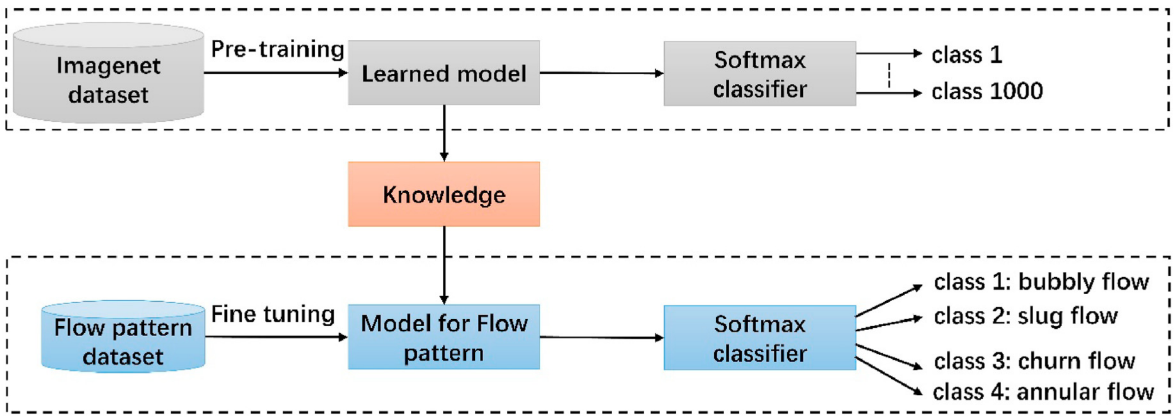

Fig. 4. Transfer learning for flow pattern online monitoring system.

Table 2
Options setting of AlexNet fine-tuning training.

	Parameters
Optimizer.	SGDM
Momentum.	0.9
Initial learning rate.	0.0001
L2 Regularization Factor.	0.0001
Mini-batch size.	20
Epoch.	20

oscillation become smaller and smaller when the iteration went deeper. After around 300 iterations, the oscillation was almost negligible, and simultaneously the accuracy for the training dataset (see Fig. 5(b)) approached 100.0%. The convergence of loss function to 0.0 and the accuracy to 1.0 indicate adequate training of CNN. Therefore, CNN has learned to classify training data correctly.

The loss function values of the test (validation) dataset in Fig. 5(a) were less than 0.1 after about 180 iterations, and their corresponding accuracy is approximately 98% in Fig. 5(b). Furthermore, the values for the test (validation) dataset were comparable with the corresponding values of the training dataset, which means the overfitting was not obvious for the given two-phase flow pattern dataset.

4. Analysis of the adaptability of CNNs

For the development of a two-phase flow pattern online monitoring system, the potential candidates of CNNs should be analyzed for their adaptability to this system, since the adopted algorithm needs to satisfy the basic requirements for the system: high precision, fast classification, strong robustness. This section will focus on the adaptability analysis of potential CNNs, which is based on MATLAB and its “Deep Learning Toolbox”. All the CNN methodologies in this study have been already trained and can be directly used in MATLAB. The transfer learning (see section 3.2) is achieved by the following three steps: (a) load the structure of the selected CNN; (b) get the parameters of the CNN fully connected (FC) layers, which contain the unique and most crucial information for image classification; (c) combine the CNN information and two-phase flow patterns base by using transfer learning to build a new classifier for flow pattern identification. The new classifier has much less parameters than the original CNN.

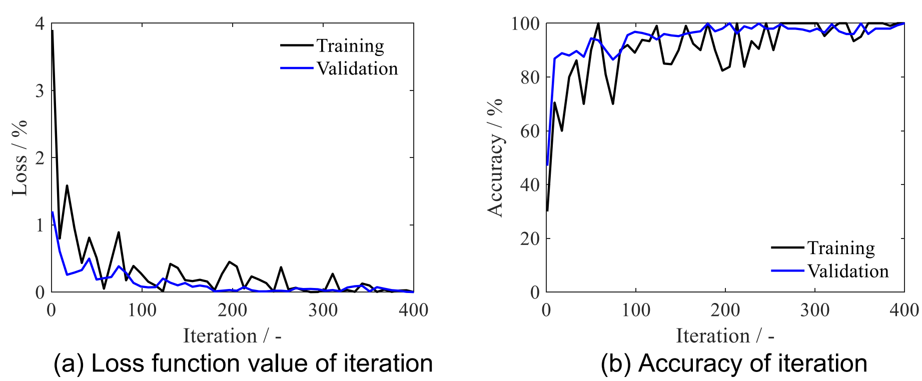

Fig. 5. Loss and accuracy during iterations of fine-tuning training.

It should be noted that the calculation in this section is based on the same computing environment. All calculation results are relatively compared with each other. But due to the limitations of the computing environment, it cannot be compared with the results of other high-performance computing. Nevertheless, it can already meet the requirements of our preliminary research. A more detailed comparison and selection of the algorithm for the online monitoring system need to be done in the future before the engineering practice of the system.

4.1. Dataset and pre-processing

To analyze the adaptability of potential CNN candidates for the online monitoring system, a dataset related to vertical upward two-phase flow patterns (with a total of 564 images) was chosen for the study. These images were classified into 4 typical flow patterns (bubbly flow 149 images, slug flow 144 images, churn flow 147 images and annular flow 124 images, respectively). A representative image for each flow pattern is shown in Fig. 6. It should be emphasized that since the flow pattern online monitoring system is under design currently and the objective of this work is to verify the adaptability of the CNN method for flow pattern identification and select the potential CNN network to support the preliminary system design, the images of the dataset was selected from the literature for the preliminary study in this work. The details of the related experimental facility can be found in [47]. It consists of a transparent test section with an inner diameter of 12.7 mm and a length of 0.89 m. The different flow patterns were generated by systematically varying air and water flow rates in a range of 0.001–0.2 kg/min and 1–10 kg/min, respectively. The system temperature is maintained between 20°C and 25°C, and the system pressure is found to vary between 1 and 3 bar.

Deep learning requires a lot of data for training. But sometimes the images for accessible datasets may be limited. Considering the limited images of the flow pattern dataset, except for the use of transfer learning method, some other enhancement measures were adopted to improve the ability of network classification, such as image augmentation (translation, rotation, and resizing, etc.) and cross-validation [48] to reduce the variance and avoid overfitting (in this study, 10-fold cross-validation was implemented).

It should be emphasized that although the difference between the Imagenet dataset and the two-phase flow pattern dataset is significant based on the superficial characterization, the underlying architectures and characterization of the images have a lot in common, which guarantee the success of transfer learning. Before the study in this article, the authors have proved the effectiveness in the transfer learning in the flow pattern identification [49].

4.2. Network comparison

In our preliminary analysis, all of the 6 CNNs in Table .1 were evaluated on their performance for flow pattern identification. By using the flow pattern dataset described in section 4.1, the results are shown in Table .3. All of the networks achieved high accuracies higher than 95%, except for VggNet16. The SqueezeNet network got the highest accuracy at 98.8%. From the viewpoint of calculation time (which means the number of images classified in 1s), AlexNet and VggNet16 cannot satisfy the basic requirement of 250 fps (minimum requirement for a high-speed camera [50]) and therefore, they are not considered for further discussion.

In order to enhance the randomness of the training set and test set, and compare the GoogLeNet, SqueezeNet, ResNet18 and ResNet50 in detail, the dataset was divided into 10 groups randomly for cross-validation. The results are shown in Fig. 7. In Fig. 7(a) and (b), the top value of each bar is the average accuracy and calculation time for each selected network respectively. The range of the statistical standard deviations (the black lines) of the 10-fold calculations are also shown each network. Consequently, a more general comparison among these methods can be achieved.

According to Fig. 7(a), the accuracies of networks SqueezeNet and Resnet50 are comparable (more than 98%), better than the other two networks. Moreover, the standard deviations for their accuracies are less than 2%. The recognition speed of transfer learning method for image identification depends not only on the structure of the network but also on the occupation and access of computer memory. By comparing the calculation time in Fig. 7(b), it is obvious that ResNet50 achieved the fastest recognition speed for two-phase flow identification. Another advantage of ResNet50 is that its standard deviation of the calculation time is 42, the lowest of all. This means it has the strongest robustness of all. Based on the analysis of accuracy, calculation speed and robustness, the ResNet50 network is suggested for the two-phase flow pattern online monitoring system.

4.3. Failure analysis

Although ResNet50 is suggested in our work, it is important to understand what the failures are by using it for flow pattern identification, to improve the results of the network. The confusion matrix is an important and typical measure to show the results of classification problems. The confusion matrix could summarize the

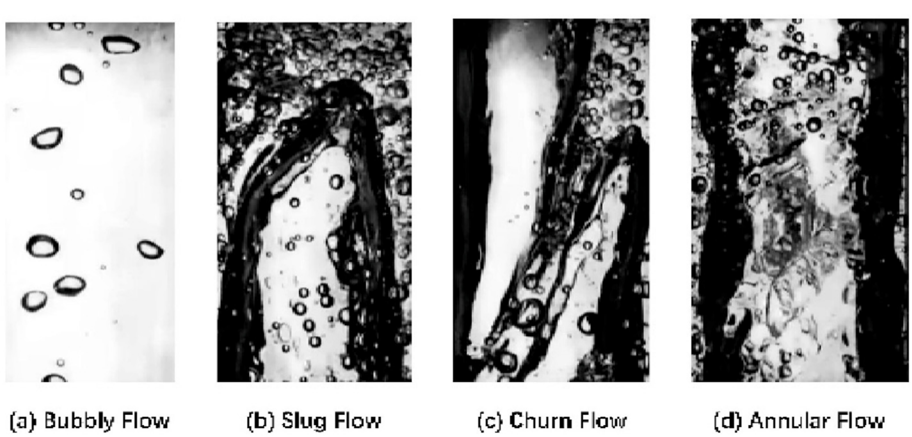

Fig. 6. Two-phase flow patterns representation in upward flow.

Table 3
Performance comparison of typical potential candidates CNNs.

	AlexNet	VggNet16	GoogLeNet	SqueezeNet	ResNet18	ResNet50
Accuracy / %	97.6	94.2	96.5	98.8	95.3	96.5
Calculation time / fps	81	94	660	273	536	1018

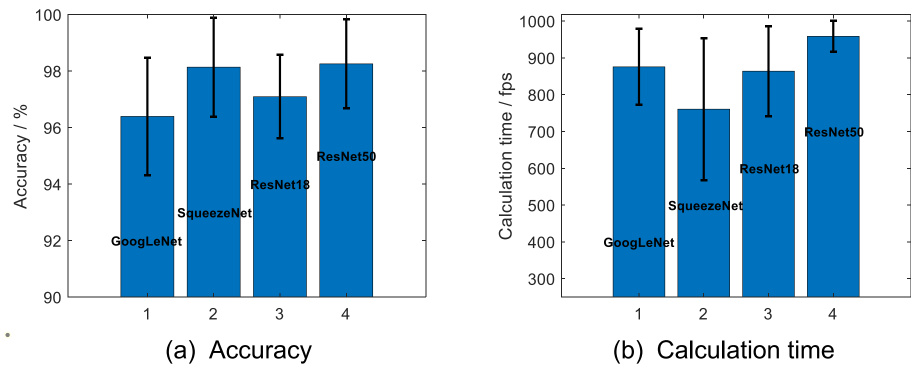

Fig. 7. The overall accuracies and calculation times of different CNN networks.

correct and incorrect classifications in a tabular form. The confusion matrix Fig. 8 shows the prediction results of 10-fold calculations (totally around 1690 results). According to Fig. 8, the following conclusions related to two-phase flow pattern identification can be obtained:

(1) since the features of bubbly flow are significant comparing with other patterns in the dataset, it can be identified by the ResNet50 network correctly.
(2) for the identification of slug flow, the accuracy of ResNet50 is 97.4%, the lowest accuracy of four flow patterns. This means the main features of slug flow can be extracted by ResNet50. But it may be misidentified for churn flow or annular flow.
(3) ResNet50 can extract the features of churn flow and get the corresponding classification. It may be misclassified for annular flow with very low probabilities. For annular flow, it has the same situation and maybe misclassified for slug flow or churn flow.

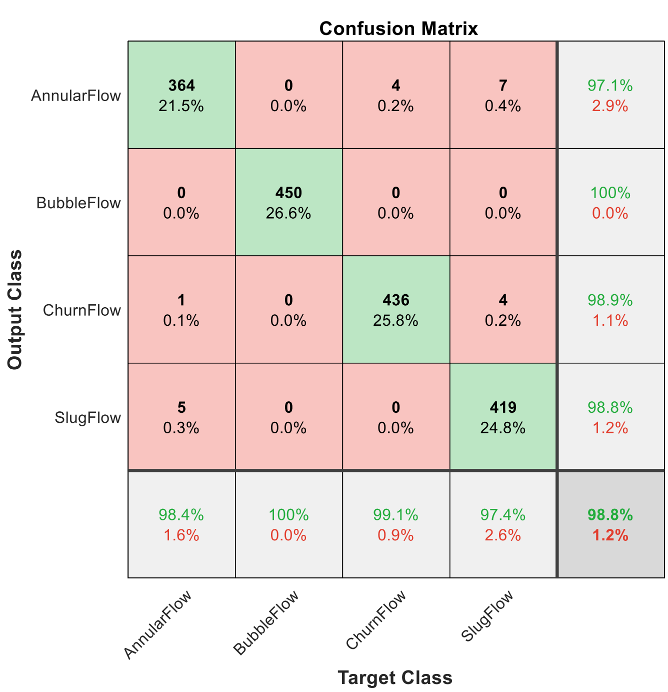

Fig. 8. Confusion matrixes for ResNet50.

According to the confusion matrix, the difficulty of the monitoring system is the identification of the slug flow owing to its instability and sensitivity for the boundary condition. It trends to transition to other flow patterns, which leads to the overlapping between these flow patterns and the difficulty of their feature extractions [51]. This type of problem could probably be addressed by introducing more slug images in the future to extract its features more accurately.

5. Conclusions

The development of a two-phase flow pattern online monitoring system was concentrated on in this work, which seldom studied before. The ongoing preliminary design (including hardware and software) of the system were introduced. As the main focus of this paper, the flow pattern identification method based on a neural network - CNN - was discussed in detail. Furthermore, in order to achieve a real-time response to the photographing, transfer learning was adopted. Several potential CNN candidates such as ALexNet, VggNet16 and ResNets were introduced and compared with each other. According to the results, ResNet50 is the most promising CNN network for the system owing to its high precision (accuracy rate higher than 98%), fast classification (image identification speed closer to 1000fps), strong robustness (best of all the candidate CNNs). Future research will focus on further validation of the proposed algorithm and the building of an online monitoring system for the two-phase flow pattern identification, to enhance the monitoring and controlling of the fluid in the experiment and energy system. Since the difficulty of the flow pattern identification is the images of slug flow owing to its instability and easy transition to other flow patterns, this topic will also be paid attention to in the future.

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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