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Key Feature Dynamic Enhancement Network for Breast Cancer Pathological Image Classification

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Abstract

Breast cancer pathological images are considered the "gold standard" for clinical diagnosis of breast cancer, but manual diagnosis suffers from inherent drawbacks such as low efficiency and high subjectivity. Computer-aided diagnosis (CAD) systems can provide objective decision support for clinicians by deeply mining multi-level features such as tissue architecture and cytology from pathological images. However, current CAD systems are still challenged by complex background noise and inconsistency in cross-scale feature representation, which hinder the extraction of critical features. Therefore, this paper proposes a key feature dynamic enhancement network for breast cancer pathological image classification (KFDE), in which the channel-spatial feature enhancement module (CSFE) and the multi-scale feature dynamic fusion module (MFDF) serve as the two core components. The CSFE module effectively suppresses background noise and highlights lesion regions through local channel variance analysis and an energy entropy-driven spatial focusing mechanism. The MFDF module employs a heterogeneous multi-branch convolutional architecture to intelligently fuse cross-scale features, addressing the issue of information fragmentation caused by magnification variation. Experiments on the BreakHis dataset demonstrate that KFDE achieves significant performance improvements, with a benign/malignant classification accuracy of 99.74% and an eight-class subtype classification accuracy of 96.35%, significantly outperforming existing mainstream models.

INTRODUCTION

According to the latest global cancer statistics, there are 2.35 million new breast cancer cases annually, accounting for 13.9% of all cancer-related deaths [1], the development of more efficient diagnostic methods has become an urgent requirement in the field of medical imaging. Traditional screening methodsmammography, magnetic resonance imaging (MRI), and ultrasound rely on indirect evaluation and often fail to accurately identify lesion details, especially in dense breast tissue or small lesions [2], [3]. H&E-stained pathological slides allow direct observation of cell-level diagnostic features and are considered the gold standard for breast cancer classification and grading [4], [5]. However, the manual examination process is complex and subjective, with studies showing an inter-observer diagnostic agreement rate of only 75.3% [6], [7].

Against this backdrop, clinical demands have driven the development of computer-aided diagnosis systems.Deep learning introduces new methods for CAD by enabling automatic extraction of tissue and cellular features.However, key feature extraction in existing CAD systems still faces limitations [8]. Primarily, feature extraction is vulnerable to background interference, where noise components such as adipose tissue and staining artifacts may obscure critical characteristics including nuclear atypia [9], [10]. Secondly, the lack of multi-scale feature dynamic fusion mechanisms makes it difficult to accommodate the hierarchical distribution of key features (coexisting at both cellular and tissue levels) and the scale inconsistency of key features caused by varying magnification levels [11]. To address this challenge, we propose the Key Feature Dynamic Enhancement (KFDE) framework. This framework constructs an input-adaptive dynamic feature enhancement mechanism that achieves background and key diagnostic feature separation through collaborative optimization of channel-spatial enhancement and multi-scale dynamic fusion. The framework incorporates two key modules which are the channel-spatial feature enhancement module (CSFE) and the multi-scale feature dynamic fusion module (MFDF). The CSFE module combines channel selection and spatial focusing to enhance model attention toward critical features while reducing noise interference. The MFDF module employs multi-branch convolution to adaptively fuse multi-scale features, performing intelligent cross-scale fusion that further strengthens the expressive capability of key features.

The main contributions of this paper include:

- To enhance the model's ability to focus on lesion areas in breast cancer pathological image classification, this paper proposes a network framework termed KFDE that effectively improves the expression of key features.
- The CSFE module integrating channel-level and spatial-level feature enhancement mechanisms is introduced to mitigate background noise interference.
- The MFDF module is introduced to achieve the joint modeling and unified representation of features at different scales, effectively addressing the expression differences of key features across different scales.
- By conducting benign/malignant classification and eight-subtype classification experiments on images with different magnification levels from the BreakHis dataset, the proposed method achieved accuracies of 99.74% and 96.35%, respectively, verifying its cross-scale consistency and stability, and demonstrating its potential in breast cancer pathological image classification.

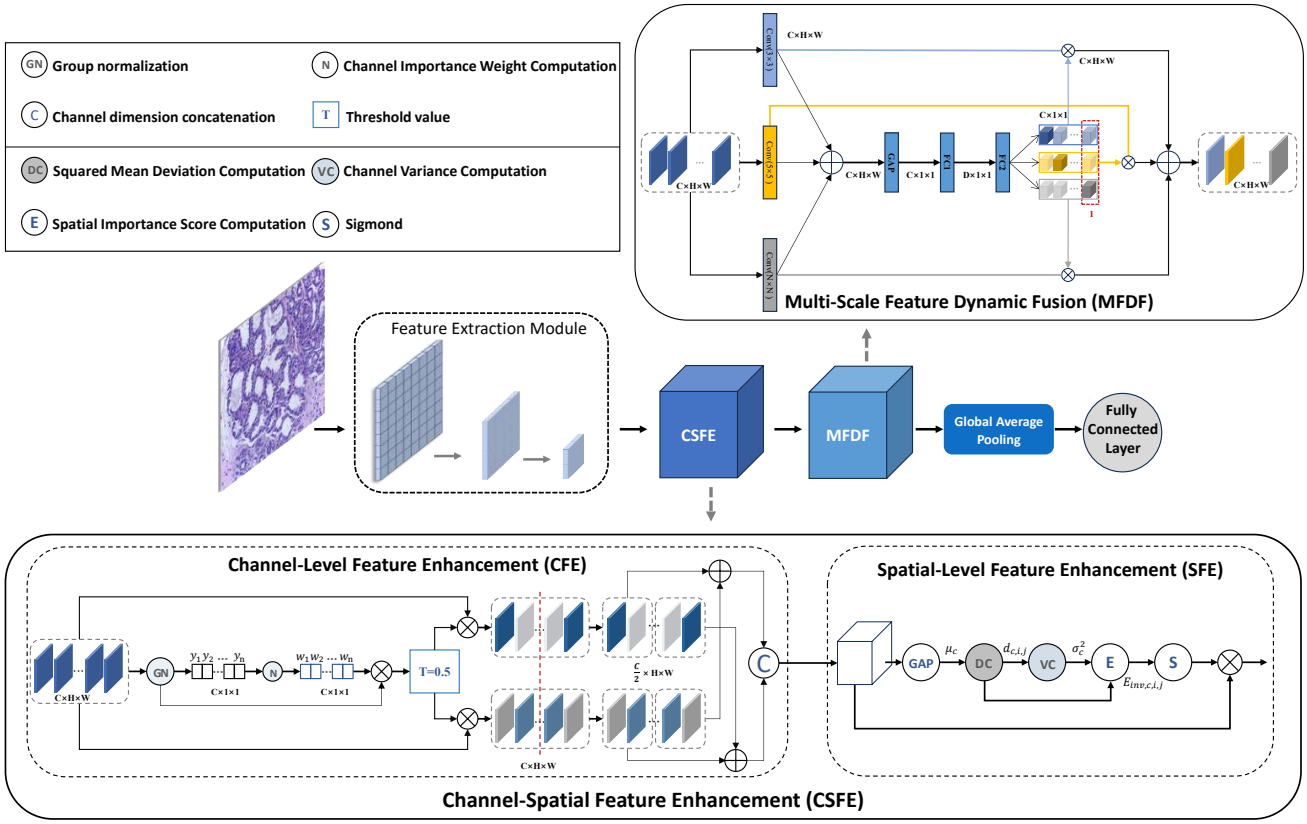

Figure 1. *The modular process of the KFDE framework. The overall architecture of the pathology logic-driven feature enhancement framework KFDE is shown: (a) ConvNeXt-V2 extracts multi-scale features via large-kernel convolutions and channel expansion, preserving high-level pathological semantics. (b) The CSFE module applies dual-branch attention (channel and spatial) for key feature selection. (c) The MFDF module deploys a multi-branch heterogeneous convolution structure, utilizing a dynamic weight allocation network to adaptively fuse cross-scale features. (d) Global feature compression and the fully connected layer output the classification probabilities based on the multi-scale fused features. Each module is designed in a cascading manner to achieve end-to-end optimization of "feature extraction - selection - fusion - decision."*

METHODS

The Overall Framework of KFDE

KFDE is designed based on a modular approach and mainly includes the CSFE module and the MFDF module. The overall framework is shown in Figure 1. The overall process is as follows:

1) Firstly, ConvNeXt-V2 serves as the backbone network to extract high-quality feature maps. Its hybrid design, combining large kernel convolution and deep channel expansion, enables robust expression of irregular nuclei and global tissue structures [12, 13].

2) Next, the CSFE module improves lesion localization by applying attention mechanisms at both the channel and spatial levels, enhancing discriminative feature representation while suppressing background noise.

3) Then, the MFDF module performs adaptive multi-scale feature extraction and fusion through a multi-branch structure, addressing the scale variance across different magnifications.

4) Finally, the optimized features are aggregated and passed through a fully connected layer to output classification results.

Channel-Spatial Feature Enhancement Module

To optimize the feature representation of key regions in breast cancer pathological images, the KFDE framework introduces the CSFE module. The CSFE module consists of dual branches, the channel branch (CFE) generates dynamic channel weights, combining with the gating mechanism for dynamic calibration, and the spatial branch (SFE) employs a lightweight design to generate spatial saliency weights.

Channel-Level Feature Enhancement Module

The CFE module aims to assess the importance of each channel, dynamically selecting and reconstructing channel features to enhance the model's ability to represent key regions. The structure of the CFE module is shown in Figure 1.

The input to the CFE module is the feature map $x \in \mathbb{R}^{N\times C\times H\times W}$ obtained after preliminary feature extraction, where N is the batch size, C is the number of channels, and H and W are the spatial dimensions of the feature map. To eliminate distributional discrepancies among channel features and stabilize the learning of channel weights, the CFE module directly applies GroupNorm normalization to the input feature map to obtain learnable channel scaling parameters γ.

Further normalization is applied to obtain the importance weight for each channel, denoted as w_{γ_i} .

$$w_{\gamma_i} = \frac{\gamma_i}{\sum_{i=1}^{C} \gamma_i} \tag{1}$$

where γ_i is the learnable parameter of the i-th channel. In this way, the importance weight for each channel is obtained.

Next, the Sigmoid function is applied to the feature map reweighted by w_{γ_i}, mapping it to the range [0, 1] to obtain the gating weight for each channel:

$$r = \text{Sigmoid}(\hat{x} \cdot w_\gamma) \tag{2}$$

To achieve selective enhancement and suppression, binarization is performed using a threshold T (set to 0.5 in the experiment), generating two different weight matrices. The calculation is as follows:

$$\mathbf{w_1} = \begin{cases} 1, & \text{if } r > T \\ r, & \text{if } r \leq T \end{cases}, \quad \mathbf{w_2} = \begin{cases} 0, & \text{if } r > T \\ r, & \text{if } r \leq T \end{cases} \tag{3}$$

The gating mechanism operates with two distinct weighting strategies: $\mathbf{w_1}$ assigns a value of 1 to salient channels to retain complete information, while $\mathbf{w_2}$ assigns a value of 0 to suppress them. The input feature x is then multiplied element-wise by $\mathbf{w_1}$ and $\mathbf{w_2}$, respectively, producing two new feature maps x_1 and x_2 The former contains rich key information, while the latter contains suppressed non-key information.

To reduce redundancy while preserving information integrity, the CFE module fuses these two to reconstruct the feature map. Specifically, it first performs channel-wise partitioning:

$$x_1 = \left[x_1^{(1)}, \quad x_1^{(2)}\right], \quad x_2 = \left[x_2^{(1)}, \quad x_2^{(2)}\right] \tag{4}$$

Then cross fuse to generate a new feature map y:

$$y = \left[x_1^{(1)} + x_2^{(2)}, \quad x_1^{(2)} + x_2^{(1)}\right] \tag{5}$$

This cross-fusion operation is designed to complement the important features with the secondary features and further enhance the expression of key information, improving the quality of the feature map.

Ultimately, the output combines channel importance weighting, gating selection, feature reconstruction and cross-fusion for enhanced representation of critical regions.

Spatial-Level Feature Enhancement Module

The SFE module enhances the representation of important spatial regions through adaptive saliency weighting, without relying on complex convolution. For input $x \in \mathbb{R}^{N \times C \times H \times W}$, saliency is computed by evaluating the squared deviation from the channel mean:

$$d_{c,ij} = (x_{c,ij} - \mu_c)^2 \tag{6}$$

where $x_{c,ij}$ is the value of the c-th channel at position (i, j), μ_c represents the mean of that channel, and $d_{c,ij}$ is the squared difference at each spatial position, reflecting the feature fluctuation at that position. The spatial variance per channel is:

$$\sigma_c^2 = \frac{1}{n} \sum_{i=1}^{n} d_{c,ij} \tag{7}$$

where $n = H \times W$ is the total number of elements in the spatial dimension of the channel. This variance reflects the distribution characteristics of each channel in the spatial dimension.

An importance score for each spatial position is then calculated as:

$$E_{\text{inv}} = \frac{d_{c,ij}}{4(\sigma_c^2 + \lambda)} + \beta \tag{8}$$

where λ is a small smoothing term to prevent division by zero, and β is a hyperparameter (set to 0.5). This score reflects the importance of each spatial position, where a higher value indicates greater contribution to the model.

Sigmoid activation generates a weight map, which is applied to the original features:

$$\hat{x} = x \cdot \text{Sigmoid}(E_{\text{inv}}) \tag{9}$$

This allows the model to emphasize salient spatial positions while suppressing irrelevant areas, enhancing feature quality with minimal computation.

Multi-Scale Feature Dynamic Fusion Module

To better capture key information at different scales in breast cancer pathological images, KFDE introduces the MFDF module. The MFDF module adopts parallel convolutional branches combined with an adaptive attention mechanism to effectively fuse local and global information.

For the input feature map $X \in \mathbb{R}^{N \times C \times H \times W}$, to effectively capture multi-scale information, MFDF uses convolution kernels of various sizes to extract features(the number and size of convolution kernels are dynamically designed based on the task in the experiment.) Each branch produces a feature map $X_k \in \mathbb{R}^{N \times C \times H \times W}$, and the multi-scale features are fused by summation:

$$\hat{X} = \sum_{k=1}^{K} X_k \tag{10}$$

where K is the number of convolution branches.

Then, by calculating the spatial average for each channel, thereby further extracting the global information of each channel:

$$p_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} f_{c,ij} \tag{11}$$

where p_c is the global average of the c-th channel, and $f_{c,ij}$ is the feature value of the c-th channel at the spatial position (i, j). A

fully connected layer (fc1) is used to reduce the dimensionality of the pooled features, mapping them from a higher-dimensional space to a lower-dimensional space $c \in \mathbb{R}^{N\times d}$:

$$c = fc1(p) \tag{12}$$

The adaptive attention mechanism uses a fully connected layer (fc2) compute the attention weight for the feature map of each branch, which is then normalized using the Softmax function:

$$\alpha_k = \text{softmax}(fc2_k(c)) \tag{13}$$

where $\alpha_k = [\alpha_{k1}, \alpha_{k2}, \ldots, \alpha_{kc}]$, is the attention weight of the k-th convolution branch, and $\alpha_{kc} \in \mathbb{R}^{N\times 1}$ is the c-th element of α_k, representing the contribution of the feature at scale k to the final output.

After computing attention weights for each scale, the final output feature map F is obtained by weighted summation:

$$F_c = \sum_{k=1}^{K} \alpha_{kc} \cdot X_{kc} \tag{14}$$

The final output feature map $F = [F_1, F_2, \ldots, F_c]$, where $F_c \in \mathbb{R}^{N\times H\times W}$, is the sum of the weighted feature maps from all convolution branches.

The MFDF module can effectively capture information at different scales and automatically adjust the contribution of each convolution branch, avoiding interference from redundant information.

Experients

Dataset

In this study, the BreakHis dataset [14] was used, which contains 7,909 breast cancer pathological images from 82 patients. The images in the dataset were captured using four different magnifications (40X, 100X, 200X, 400X), covering two types of lesions (benign and malignant) and eight different pathological types. Specifically, the dataset contains 2,480 benign tumor images, including adenoma, fibroadenoma, phyllodes tumor, and tubular adenoma, and 5,429 malignant tumor images, including ductal carcinoma, lobular carcinoma, mucinous carcinoma, and papillary carcinoma [14].

Results and Analysis

Comparative Experiments

In the comparative experiments, common CNN architectures such as ResNet-50, VGG-16, and DenseNet-121 are used as reference models for comparison, all following the same data preprocessing and splitting strategy to ensure fairness.

Additionally, the proposed KFDE is compared with several representative breast cancer pathology classification methods: (a) BHCNet integrates residual andSEblocks to reduce parameters, designs a lightweight mini SE-ResNet module, and proposes a Gaussian error scheduler to automatically adjust the learning rate [15]; (b) BreastNet integrates the CBAM attention module, hypercolumn multi-scale features, and residual blocks to enhance focus on critical regions through channel and spatial attention [16].

Table 1: Benign Versus Malignant Classification Results

Method	Results(ACC%)			
	40X	100X	200X	400X
VGG-16	88.20	87.90	88.21	86.32
ResNet-50	92.22	93.40	95.37	91.34
DenseNet-121	92.61	92.00	93.93	91.73
BHCNET	98.87	99.04	99.34	**98.99**
BreastNet	97.99	97.84	98.51	95.88
AHoNet	96.53	97.47	99.09	96.52
Hybrid CNN-LSTM	99.03	**99.75**	**99.64**	98.07
KFDE	**99.74**	99.56	99.60	97.88

Table 2: Eight-subtype Classification Results

Method	Results(ACC%)			
	40X	100X	200X	400X
VGG-16	87.44	85.45	83.09	82.54
ResNet-50	90.76	88.82	87.63	87.25
DenseNet-121	91.02	89.22	87.38	86.83
BHCNET	94.43	94.45	92.27	91.15
BreastNet	93.97	92.92	91.23	91.79
Hybrid CNN-LSTM	**96.50**	92.60	88.94	92.51
GLNET	90.01	92.32	91.98	91.51
KFDE	96.35	**94.52**	**92.64**	**92.67**

(c) AHoNet embeds the ECA module into ResNet18 to capture channel-wise attention, and incorporates second-order covariance statistics to extract global features for improved classification robustness [17]. (d) The CNN-LSTM hybrid model uses a pretrained CNN to extract features and an LSTM to model the temporal sequence of features, achieving a better feature representation through concatenation [18]. (e) GLNET designs a global-local feature extractor based on ResNet101, integrating whole-slide and ROI-level features to optimize multi-label classification [19].

As shown in Table 1 and Table 2, in the benign versus malignant classification task, the KFDE model achieves the highest classification accuracy of 99.74% at 40X magnification, while the accuracies at other magnifications are also close to optimal. In the eight-subtype classification task, the KFDE model achieves an accuracy of 96.35% at 40X magnification, showing a slight gap compared to the 96.5% of the Hybrid CNN-LSTM model, but it demonstrates slight improvements in accuracy (less than 1%) at other magnification levels.

Visual Explanation

To validate the effectiveness of the proposed CSFE and MFDF modules, this study employed Gradient-weighted Class Activation Mapping (Grad-CAM) to visualize test images of different magnifications and categories. Grad-CAM highlights the regions the model focuses on during classification, helping to understand the decision-making process [20].

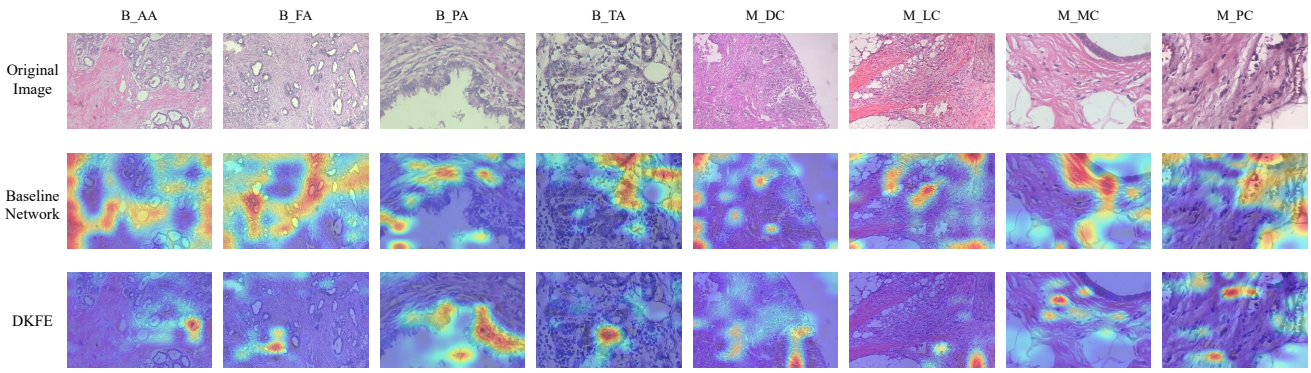

Figure 2. *Visualization results of the baseline network and KFDE. The images are from different categories and magnifications in the BreakHis dataset.*

As shown in Figure 2, the Grad-CAM results clearly demonstrate that, compared with the baseline network, the model with the proposed modules exhibits more concentrated attention, focusing more precisely on key regions that highly correspond to the lesion areas. This further indicates that the designed modules can effectively guide the model to attend to more discriminative key features.

Ablation Experiments

This study conducted a series of ablation experiments to validate the effectiveness of the CSFE and MFDF modules in breast cancer pathological image classification. The experiments gradually removed these modules and compared the performance of different model configurations to comprehensively assess the contribution of each module to classification performance. The setup of the ablation experiments is as follows:

- Baseline: Does not include the CSFE and MFDF modules, serving as the benchmark for the model.
- CSFE: The CSFE module is added to the baseline network to verify the impact of this module on model performance.
- MFDF: The MFDF module is added to the baseline network to verify the impact of this module on model performance.
- KFDE: Integrates CSFE and MFDF modules to investigate their synergistic effects.

Table 3: Ablation Study Results

Method	Results(ACC%)			
	40X	100X	200X	400X
Baseline	95.24	93.55	91.55	90.67
CSFE	96.12	93.60	92.11	91.76
MFDF	95.75	93.73	92.23	92.00
KFDE	**96.35**	**94.52**	**92.64**	**92.67**

As shown in Table 3, the experimental results indicate that both modules can independently improve the model's performance, demonstrating that CSFE enhances key information while MFDF improves the perception of multi-scale lesion regions. Moreover, when combined, the model achieves the highest classification accuracy, reflecting the synergistic advantages of key feature enhancement and multi-scale analysis.

Conclusion

This study proposes the KFDE framework, integrating CSFE and MFDF modules to effectively address key feature suppression and cross-scale expression inconsistency in breast cancer pathological image classification. The CSFE module suppresses background interference through local channel variance analysis and a spatial focusing mechanism, while the MFDF module coordinates feature representation at the cellular and tissue levels via adaptive multi-scale fusion. Experiments on the BreakHis dataset show that KFDE achieves accuracies of 99.74% and 96.35% in benign versus malignant and eight-subtype classification tasks, respectively, surpassing existing mainstream models. Visualization analysis further confirms the model's precise focus on critical lesion areas, offering interpretable decision support for clinical diagnosis. Future research will explore its transferability to pathological images of other cancer types and optimize computational efficiency.

Acknowledgment

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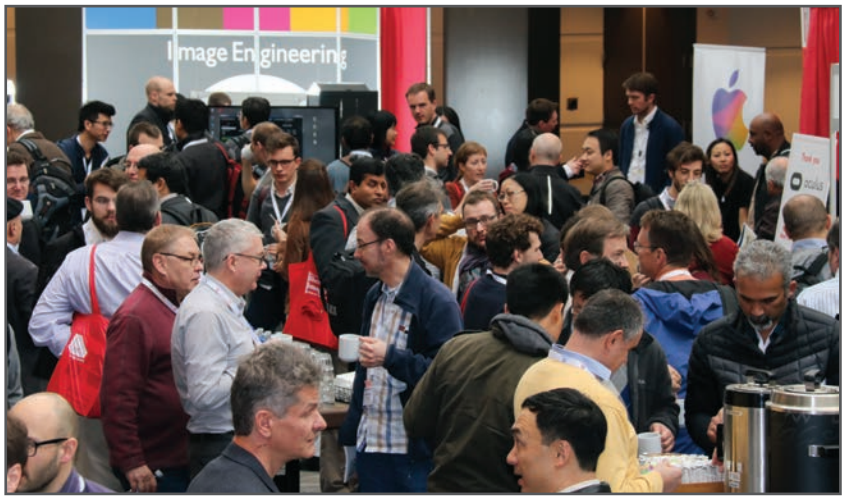

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