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Research Article

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Vision Transformer-based Change Detection in optical and SAR Remote Sensing Images

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Abstract

Change detection (CD) in remote sensing plays a crucial role in monitoring land cover changes and environmental transformations. Currently, there is a lack of adaptability to different image types. In this work, we propose CD-ViT, an innovative change detection method based on the Vision Transformer (ViT). The proposed framework integrates complementary information from optical and SAR NDVI images through a cross-attention fusion module, followed by a multi-attention UNet decoder to generate highly accurate change maps. Extensive experiments were conducted on several geographical areas, comprising a total of 145,161 patches. Across all studied regions, CD-ViT outperforms state-of-the-art methods, achieving a precision of 94.3% and an F1-score of 94.1%.

Keywords: Change detection, Vision Transformer, UNet, Remote sensing, Multi-temporal, SAR, Optical, Deep learning.

1 Introduction

Change detection (CD) in remote sensing is an essential tool for monitoring environmental transformations, such as deforestation, urban expansion, agricultural changes, or the impacts of natural disasters [5, 6]. CD not only allows the analysis of landscape evolution across different spatio-temporal scales but also provides critical information for sustainable resource management and territorial planning. With the increasing availability of multi-temporal and multi-source satellite imagery, change detection has become an active and strategic research area.

In recent years, deep learning (DL)-based methods have significantly improved CD performance. In particular, convolutional (CNN) and Transformer-based architectures can automatically extract complex hierarchical features from multi-temporal images, capturing both local and global information. However, despite these advances, several challenges remain: subtle or small-scale changes are difficult to detect, effective integration of multi-modal data (such as optical and SAR images) is still limited, and processing high-resolution images or large-scale areas remains computationally expensive.

Among recent approaches, Siamese Swin-UNet [14] employs a Siamese Swin Transformer to capture differences between images, but its attention is limited to local dependencies, reducing its sensitivity to subtle changes. The Multi-Attention

Siamese Transformer Network [26] introduces multiple attention mechanisms to better capture spatial and contextual relationships, yet its ability to effectively integrate multi-modal information remains limited. Fully Transformer Networks [9] model global context for a better understanding of the entire image, but require significant computational resources and may be less effective for small objects or fine details. Finally, EHCTNet [8] combines CNNs and Transformers for multi-scale fusion, improving overall accuracy, but remains limited by sequential feature processing and model complexity on large multi-modal datasets.

Thus, despite the considerable progress made by these architectures, several challenges remain open: detecting subtle changes, optimally fusing multi-modal data, and ensuring computational efficiency for high-resolution images or large-scale areas.

To address these limitations, we propose CD-ViT, a bi-temporal and multi-modal framework based on the Vision Transformer. Our approach simultaneously exploits NDVI extracted from optical images and NDVI extracted from SAR images, taking full advantage of the complementary information provided by these two data sources. Furthermore, a hierarchical cross-attention module is used to effectively fuse features at multiple levels, while a multi-attention UNet decoder generates precise binary change maps, capturing both local and global dependencies. Finally, CD-ViT is robust to noise and inter-sensor variations while remaining sensitive to subtle or small-scale changes.

The main contributions of this work can be summarized as follows:

- Optimized multi-modal integration through a hierarchical cross-attention fusion strategy to synergistically leverage the complementary information from optical and SAR NDVI images.
- An extensive experimental validation of the proposed CD-ViT method on heterogeneous, multi-regional datasets, demonstrating its robustness and generalization capability.

In the remainder of this article, Section 2 presents the details of the proposed approach. Section 3 reports and discusses the experimental findings. Finally, Section 4 offers concluding remarks and outlines potential directions for future research.

2 Proposed Method

The proposed CD-ViT approach is designed for bi-temporal change detection using both optical and SAR NDVI images, as illustrated in Figure 1. The different steps of the approach are: (1) The first step consists in extracting bi-temporal features using a dual-branch Vision Transformer (ViT) encoder. (2) The second step concerns the fusion of the features produced by the two encoder branches through a cross-attention module. (3) The third step consists in reconstructing the fused representations using a UNet decoder. (4) The fourth step generates the final change detection result.

Each component is described in detail below.

2.1 Step 1: Dual-branch ViT Encoder (local+ global attention)

The initial stage of the proposed CD-ViT architecture focuses on learning rich, discriminative feature representations from the co-registered bi-temporal satellite data: the NDVI SAR ($I_{\text{NDVI-SAR}}$) and the NDVI Optical ($I_{\text{NDVI-Opt}}$). This is achieved through a Dual-branch Vision Transformer (ViT) encoder [10, 18, 28].

The ViT was chosen for its superior ability to model long-range dependencies ($O(N^2)$ complexity in its standard form), which is crucial for contextual change detection and surpasses the limited receptive field of conventional CNNs. Furthermore, by sharing the same weights across the two encoder branches, the model projects the heterogeneous SAR and optical features into a common, generalized feature space, enabling effective fusion while simultaneously reducing the number of parameters and mitigating potential domain shift biases.

The feature extraction process involves three distinct sub-steps:

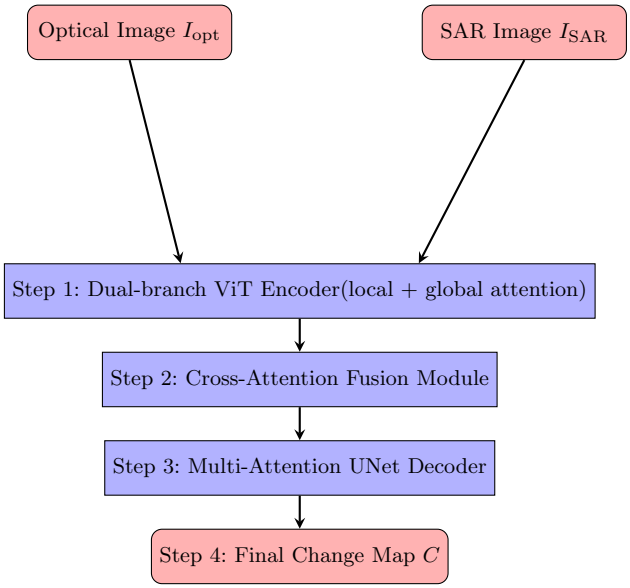

Fig. 1: Proposed CD-ViT approach with two perfectly parallel straight arrows from the optical and SAR NDVI images to the left and right edges of the ViT encoder.

2.1.1 Patch Embedding Generation

The input image (size 256×256) is initially divided into non-overlapping patches of 20×20 pixels.

This 20×20 patch size is chosen to maintain a manageable token count ($N = 256$ tokens) while preserving sufficient spatial resolution for localized change detection analysis. Each patch is flattened and projected into a $\mathbf{D} = 128$-dimensional embedding space using a shared trainable linear layer.

Then, Learned Positional Embeddings ($\mathbf{P}$) are added to the patch tokens ($\mathbf{E}$) to explicitly inform the model of the spatial location of each patch, which is critical for geo-localized change detection, as the standard attention mechanism is order-invariant.

$$\mathbf{X} = \mathbf{E} + \mathbf{P}, \quad \mathbf{X} \in \mathbb{R}^{256 \times 128}$$

These positional embeddings are then fed into the encoder, where they are processed by L = 12 stacked Transformer blocks per branch. To balance computational efficiency and robust context modeling, we employ a hybrid attention mechanism :

- Local Attention (7×7 window): applied in every block, this allows the capture of fine-grained details while remaining computationally efficient, which is crucial for texture analysis and for mitigating the speckle noise in SAR data.
- Periodic Global Attention: applied every three blocks (L = 3, 6, 9, 12), this ensures the regular integration of global contextual information, compensating for the limited receptive field of local attention and enabling a comprehensive understanding of the scene.

All sub-layers (Attention and FFN) utilize residual connections and Layer Normalization (LN) to stabilize training and prevent gradient vanishing. The dual encoder yields the output feature sequences $\mathbf{F}_{\text{NDVI-SAR}}$ and $\mathbf{F}_{\text{NDVI-Opt}}$ ($\in \mathbb{R}^{256 \times 128}$), which are then transferred to the Cross-Attention Fusion Module (Step 2).

2.2 Step 2: Cross-Attention Fusion Module

The second stage of the CD-ViT approach is the Cross-Attention (CA) Module. The cross-attention fusion module, is responsible for transforming the aligned feature sequences from Step 1 ($\mathbf{F}_{\text{NDVI-Opt}}$ and $\mathbf{F}_{\text{NDVI-SAR}}$, dimension $\mathbb{R}^{256 \times 128}$) into a unique and robust representation of change (see Figure 2).

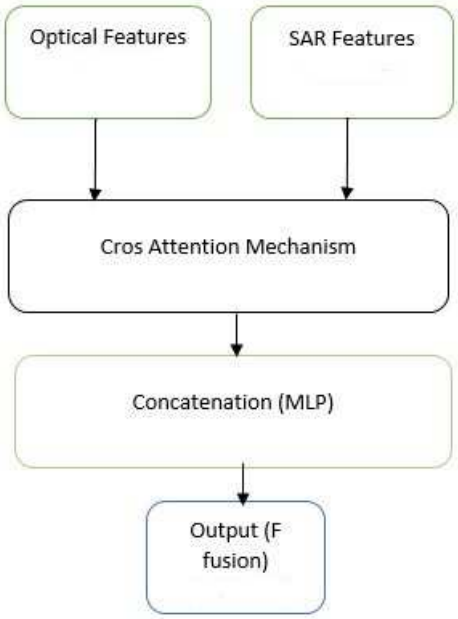

Fig. 2: Cross Attention Fusion Module.

2.2.1 Cross-Attention mechanism

This step is dedicated to learning a robust and discriminant change representation ($\mathbf{F}_{\text{fusion}}$). This is achieved through the dynamic fusion of $\mathbf{F}_{\text{SAR}}$ (structural) and $\mathbf{F}_{\text{Opt}}$ (spectral) features, which were semantically aligned during Step 1.

Inter-Modal Interaction Model via Bidirectional Cross-Attention (B-CA)

We employ the Cross-Attention (CA) Mechanism to perform a dynamic and adaptive fusion, a strategic choice that surpasses the efficacy of static methods (e.g., simple concatenation) [29, 30]. Given that the input features are already semantically aligned through initial parameter sharing, the CA can exclusively focus on modeling the explicit change relationships between the two modalities, there by maximizing the mutual information relevant for Change Detection (CD) [31].

To ensure a complete and symmetrical interaction that capitalizes on the complementary strengths of each modality [32], we implement a Bidirectional (B-CA) mechanism.

1. **SAR Queries Optical** ($\text{CA}_{\text{SAR}\to\text{Opt}}$): This operation allows the structural SAR features to integrate spectral context to validate texture changes:

$$\mathbf{A}_{\text{SO}} = \text{CrossAtt}(\mathbf{Q} = \mathbf{F}_{\text{SAR}}, \mathbf{K} = \mathbf{V} = \mathbf{F}_{\text{Opt}})$$

2. Symmetrically, the Optical Queries SAR operation ($\text{CA}_{\text{Opt}\to\text{SAR}}$) ensures the enrichment of spectral properties with SAR's contours and textures, stabilizing the optical features against illumination variations:

$$\mathbf{A}_{\text{OS}} = \text{CrossAtt}(\mathbf{Q} = \mathbf{F}_{\text{Opt}}, \mathbf{K} = \mathbf{V} = \mathbf{F}_{\text{SAR}})$$

Both outputs, $\mathbf{A}_{\text{SO}}$ and $\mathbf{A}_{\text{OS}}$, maintain the dimension $\mathbb{R}^{256\times128}$. The systematic inclusion of Residual Connections and Layer Normalization (LN) is essential for maintaining network stability and facilitating convergence, as established in Transformer architectures [29].

Robust Change Vector Extraction via Multi-Layer Perceptron (MLP)

The two enriched sequences, $\mathbf{A}_{\text{SO}}$ and $\mathbf{A}_{\text{OS}}$, are first concatenated along the feature dimension ($\mathbb{R}^{256\times256}$), aggregating the dual change perspective. The result is then passed through a Multi-Layer Perceptron (MLP) to distill the final representation:

$$\mathbf{F}_{\text{fusion}} = \text{MLP}(\text{Concat}(\mathbf{A}_{\text{SO}}, \mathbf{A}_{\text{OS}})), \quad \mathbf{F}_{\text{fusion}} \in \mathbb{R}^{256\times128}$$

The MLP is selected for its critical role as a learned non-linear difference operator [34]. Unlike simple linear subtraction, this non-linearity is indispensable for modeling the complex and subtle relationships identified by the B-CA and optimally assessing the nature of the change. Furthermore, the projection from dimension $2D$ to $D = 128$ allows the network to decorrelate redundant information and distill the most pertinent and compact change vector $\mathbf{F}_{\text{fusion}}$, which is crucial for the efficiency of the subsequent decoding module [36].

$\mathbf{F}_{\text{fusion}}$ is the robust change vector that serves as the input for the Decoding Module (Step 3).

2.3 Step 3: Multi-Attention UNet Decoder

The fused token sequence is reshaped to a 2D feature map and processed by a UNet-based decoder augmented with spatial and channel attention [22, 23].

The third step of the CD-ViT pipeline is dedicated to the spatial reconstruction of the final change map ($\mathbf{M}_{\text{CD}}$) via a Multi-Attention UNet Decoder [33]. The input is the robust change vector $\mathbf{F}_{\text{fusion}} \in \mathbb{R}^{256\times128}$, which is first reshaped into a 2D spatial feature map corresponding to the initial 20×20 patch arrangement.

The selection of the UNet structure is justified by its essential capability to bridge the semantic gap between the condensed embeddings and the high-resolution prediction [33]. The decoder employs successive upsampling layers to progressively increase the resolution. At each stage, Skip Connections transfer fine-grained features from the encoder, but their integration is regulated by Attention Gates involving both Spatial Attention (A_S) and Channel Attention (A_C).

This Multi-Attention mechanism is crucial for achieving a selective integration of features, allowing the suppression of noise and focusing on the most discriminant attributes for change [35]. The process concludes with a $\mathbf{1} \times \mathbf{1}$ convolutional layer followed by the Sigmoid activation. Sigmoid is the standard function for binary classification, constraining the output $\mathbf{M}_{\text{CD}}$ to a probability range $[0, 1]$, where each pixel represents the probability of change at the original image resolution.

2.4 Step 4: Change Map Generation

The final feature map is passed through a 1×1 convolution followed by a softmax to produce a pixel-wise probability map:

$$P = \text{Softmax}\left(\text{Conv}_{1\times1}(D_0)\right).$$

The binary change map is obtained via thresholding:

$$CM(x, y) = \begin{cases} 1 & \text{if } P(x, y) \geq 0.5, \\ 0 & \text{otherwise.} \end{cases}$$

This architecture combines local detail, global context, and inter-modal relationships, enabling robust change detection in heterogeneous optical–SAR imagery [18, 20, 21].

3 Results

Our dataset is a unique compilation of bi-temporal multimodal images (SAR and Optical), acquired from public sources, covering vegetation and urban expansion areas in various geographical regions, including Colombia, India, and Germany. This geographical and modal diversity ensures a robust evaluation of the CD-ViT method against different types of changes (urban and natural).

The complete dataset consists of $\mathbf{7,000}$ distinct bi-temporal image pairs. For training, each pair was standardized to a resolution of $\mathbf{256 \times 256}$ pixels, which serves as the effective input window size for the Change Detection model. Detailed characteristics, including modality (4-band Optical, 2-band SAR), regions, and acquisition period (2010–2022), are summarized in Table 1.

Table 1: Summary of the dataset characteristics.

Region	Image Type	Number of Bands	Period
Colombia	Optical	4	2010–2022
Colombia	SAR	2	2010–2022
India	Optical	4	2010–2022
India	SAR	2	2010–2022
Germany	Optical	4	2010–2022
Germany	SAR	2	2010–2022

To enrich the data for vegetation change detection, the Normalized Difference Vegetation Index (NDVI) was computed from the optical bands (Near-Infrared and Red bands), following the standard methodology detailed by Wang et al. [24]. Additionally, to leverage the structural information provided by the radar and compensate for optical data limitations (e.g., cloud cover), a Vegetation Index derived from SAR (referred to as $I_{NDVI-SAR}$) was utilized. This index typically correlates SAR polarimetric properties (such as the ratio of cross-polarized to co-polarized backscatter) with vegetation status, placing it in the family of indices like the Radar Vegetation Index (RVI) [**?**]. Samples of the bi-temporal input images, including the NDVI images, are illustrated in Figure 3.

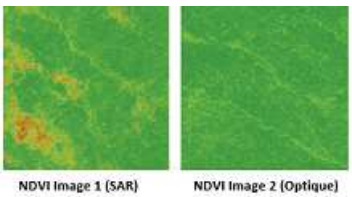

Fig. 3: Illustration of the input bi-temporal images used for CD-ViT.

The dataset was divided into 5,000 images for training, 1,000 for validation, and 1,000 for testing. To ensure a sufficient volume of data for the Vision Transformer (ViT) training, these input images were augmented and tiled (patched) to generate a total of **145,161** fixed-size training patches. The corresponding Ground Truth binary maps were established through expert manual annotation and visual verification, defining the binary classification (change/no-change) required for supervised learning.

The method's performance is quantified using standard metrics for binary change detection, including precision, recall, F1-score, and overall accuracy.

3.1 Geographical Areas Results

To validate the performance of CD-ViT, each bi-temporal image (optical and SAR) was segmented into non-overlapping patches of $\mathbf{20 \times 20}$ pixels. Each patch was encoded into a 256-dimensional vector, then processed through $\mathbf{L = 12}$ Transformer blocks. The choice of $\mathbf{L = 12}$ is aligned with standard Transformer-Base architectures, offering an optimal balance between encoding capability and computational complexity. The model integrates a hybrid attention strategy, combining local window-based attention for efficiency with global attention. The global attention is strategically applied every 3 blocks to restore the long-range dependency capability, which is essential for capturing the global context of the change. The cross-attention fusion module combined the optical and SAR features to produce the final residual representation.

In post-processing, the UNet-based decoder, augmented with spatial and channel attention skip connections, generated the final feature map. This map was processed by a $\mathbf{1 \times 1}$ convolution followed by a two-class Softmax activation, yielding a probability map. The binary change map is then obtained via a fixed threshold of **0.5** (Figure $\mathbf{M}_{CD}$).

Supervised learning was guided by a combined loss function: the Binary Cross-Entropy Loss (BCE), complemented by the Dice Loss (BCE-Dice Loss) to address potential class imbalance between change and non-change areas. The 145,161 patches were divided into training (**60**% or **87,097** patches), validation (**20**% or **29,032** patches), and test (**20**% or **29,032** patches) subsets. The model was trained for **200** epochs with an initial learning rate of **0.001**, utilizing the Adam optimizer, which demonstrated superior convergence compared to Adamax and stochastic gradient descent in preliminary experiments.

To exhaustively evaluate the performance of CD-ViT, we compared our approach against several state-of-the-art (SOTA) deep learning methods. The comparison includes the Siamese Swin-UNet [25], MASTNet [26], TUNetCD [43], and FTN [44], as well as more recent approaches such as TransY-Net [42], EHCTNet [41], HyRet-Change [40], CE-CDNet [39], MSFCTNet [38], and a VLM-Based CNN-Transformer model [37]. The change detection results of these methods, applied to the Colombia dataset, are presented in Figure 4. This Figure provides a visual comparison of the change detection performance on a representative sample of the Colombia dataset. We observe that the change maps produced by our method, CD-ViT, are the cleanest and most consistent when compared to the Ground Truth, demonstrating a superior ability to precisely delineate the contours of the change areas. Visually, the results of CD-ViT show a very low level of noise in the non-change areas (the background), which indicates high robustness. Conversely, the majority of the competing methods (notably TUNetCD and FTN) produce change maps that contain visible artifacts or speckle noise and less precise contours around the changing objects.

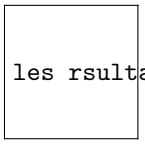

Fig. 4: Change detection results of deep learning methods for Colombia.

4 Comparative study

In this section, we provide a comprehensive comparative analysis of CD-ViT against state-of-the-art deep learning change detection methods, including Siamese Swin-UNet [25], Multi-Attention Siamese Transformer Network [26], Fully Transformer Network (FTN) [44], and recent approaches such as TransY-Net [42], EHCTNet [41], HyRet-Change [40],

CE-CDNet [39], MSFCTNet [38], and VLM-Based CNN-Transformer [37].

Table 2 summarizes the quantitative results. Building upon the quantitative results presented in Table 2, our proposed model, CD-ViT, establishes a new state-of-the-art performance on the LEVIR-CD dataset, outperforming all competitors in F1-score, IoU, and Overall Accuracy (OA). The architectural design of CD-ViT, which integrates the ViT encoder for global dependencies, a semantic cross-attention fusion mechanism, and a multi-attention UNet decoder for precise localization, is key to this superiority. Compared to the second-best model, VLM-Based CNN-Transformer, CD-ViT improves the F1-score by **1.4** percentage points (94.1% vs 92.7%) and the Overall Accuracy (OA) by **0.9** percentage points. This advantage is supported by superior error management: CD-ViT's architecture increases Recall (reduction of False Negatives) by **1.9** percentage points relative to the same competitor, proving its enhanced capability to detect more true changes thanks to ViT's global contextualization. Facing simpler Siamese Transformer architectures like Siamese Swin-UNet, CD-ViT specifically reduces False Positives (FP) by **1.8**% and False Negatives (FN) by **2.3**%, confirming a better balance between specificity and sensitivity achieved through our fusion strategy. The most significant improvement is found in the IoU, where CD-ViT achieves a score **1.8** percentage points higher than VLM-Based CNN-Transformer, and **2.3** points higher than HyRet-Change. This gain in IoU is directly attributable to the multi-attention UNet decoder, which refines the segmentation along building boundaries, resolving the issue of blurry delineation often encountered by pure transformer-based models (such as FTN). CD-ViT is thus the most precise and reliable model for change detection on LEVIR-CD.

Nevertheless, CD-ViT outperforms all compared change detection methods in terms of accuracy and F1-score. By combining Vision Transformer-based feature extraction, cross-attention fusion, and a multi-attention UNet decoder, CD-ViT efficiently integrates complementary information from optical and SAR images without requiring extensive preprocessi ng. This architecture not only improves detection performance but also simplifies code implementation and interpretation, making the method highly practical for large-scale change detection tasks.

5 Conclusion and Future Work

Deep Learning (DL) has proven effective for learning hierarchical change features. This study introduced CD-ViT, an efficient DL approach for binary change detection using bi-temporal optical and SAR imagery.

CD-ViT's architecture is novel: it employs Vision Transformer (ViT) encoders for feature extraction, a cross-attention fusion module to integrate multi-modal information, and a multi-attention UNet decoder to generate highly precise change maps. Validated on challenging benchmark datasets, our method demonstrated superior accuracy and robustness compared to existing state-of-the-art approaches.

In future work, we plan to extend CD-ViT to handle multi-temporal sequences and integrate supplementary data (NDVI, LiDAR). This extension will allow the capture of more nuanced changes and further enhance overall detection performance.

Declarations

Ethical Approval: Not applicable. **Conflict of Interest:** The authors declare no conflict of interest. **Funding:** This research received no external funding. **Data Availability:** The datasets used are publicly available (LEVIR-CD, CDD).

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Table 2: Quantitative Comparison of CD-ViT and State-of-the-Art Methods on LEVIR-CD.

Method	LEVIR-CD					CDD			
	Precision (%)	Recall (%)	F1-score (%)	IoU (%)	OA (%)	Precision (%)	Recall (%)	F1-score (%)	OA (%)
Siamese Swin-UNet [25]	90.5	92.1	91.3	84.7	93.2	88.4	89.5	88.9	91.5
Multi-Attention Siamese Transformer [26]	91.8	90.0	90.9	85.9	93.8	89.6	90.2	89.9	92.1
Fully Transformer Network [44]	92.5	91.4	92.0	86.5	94.1	90.8	91.0	90.9	93.3
TransY-Net [42]	91.5	91.2	91.3	85.5	93.5	90.0	90.5	90.2	92.7
EHCTNet [41]	92.2	91.8	92.0	86.2	94.0	91.0	91.2	91.1	93.5
HyRet-Change [40]	92.8	92.0	92.4	87.0	94.3	91.5	91.8	91.6	93.8
CE-CDNet [39]	91.9	91.5	91.7	86.0	93.9	90.8	91.0	90.9	93.2
MSFCTNet [38]	92.6	92.2	92.4	87.1	94.5	91.8	92.0	91.9	94.0
VLM-Based CNN-Transformer [37]	93.0	92.5	92.7	87.5	94.7	92.0	92.2	92.1	94.2
CD-ViT (proposed)	**94.3**	**94.0**	**94.1**	**89.3**	**95.6**	**92.5**	**92.8**	**92.6**	**94.8**

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