

Multi-scale local perception video topic recognition method based on semantic-guided feature pyramid

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Abstract. Video topic recognition faces core challenges such as the limitations of static representations, cross-modal semantic misalignment, insufficient coverage of single-scale features, and weak temporal dynamic modeling. This paper finds that existing methods have significant deficiencies in local detail perception, leading to the neglect of key local cues such as "test tubes" in "laboratory" scenes, or the inability to simultaneously capture global environment and local details in "wedding" scenes. To address this, we propose a semantic-guided multi-scale feature pyramid learning method. The core innovation lies in the design of a temporal-semantic guided multi-scale local feature extractor (MLFE). This module can not only handle spatial multi-scale features but also incorporate temporal dynamics and textual semantic guidance to achieve adaptive scale selection. Based on this, we have constructed a complete recognition framework, including an improved cross-frame communication mechanism and a multi-granularity dynamic cue generation module. Experiments on benchmark datasets such as Kinetics-400 and Kinetics-600 show that our method significantly outperforms existing methods in scenarios requiring fine-grained local feature recognition, especially in topics such as "laboratory," "medical surgery," and "cooking process."

Keywords: Video topic recognition, multi-scale local perception, feature pyramid network, semantic-visual alignment, local feature enhancement

1 Introduction

With the explosive growth of video data, video topic recognition, as a core task in cross-modal understanding, holds significant application value in fields such as intelligent surveillance, content retrieval, and recommendation systems[1]. Unlike single-frame image recognition, the definition of video topics relies on four core characteristics: dynamic coherence (such as "marathon" requiring the sequential actions of starting, running, and finishing to be connected)[2], modal semantic alignment (such as "academic speech" requiring the association of textual abstract semantics with video concrete scenes)[3], multi-scale feature coverage (such as "wedding" requiring consideration of both the global scene and local cues like rings and wedding dresses)[4], and temporal

association modeling (such as "cooking" requiring the capture of the process evolution from ingredient processing to cooking to finished product)[5].

Existing video topic recognition methods have significant limitations: 1) Traditional single-frame models (such as CLIP[6]) divide videos into independent frames for processing, ignoring inter-frame dependencies, leading to misidentification of dynamic topics (e.g., a single frame of a "player shooting a ball" is misidentified as "fitness"); 2) Fixed Prompt cannot adapt to the dynamic details of videos, resulting in semantic-visual mismatch (e.g., the text "concert" is difficult to align with the video of "a street performer playing music") [7]; 3) Single-scale feature extraction can only cover global or local information, leading to the omission of topic clues (e.g., the "laboratory" scene ignores the key local feature "test tube") [8]; 4) Inter-frame temporal information is processed in isolation, unable to capture the dynamic evolution of topics (e.g., using only the "crossing the finish line" frame leads to the misidentification of "marathon" as "track and field competition") [9][10]. The TimeSformer model proposed by Bertasius et al. [11] innovatively extends the self-attention mechanism of Transformer [12] to the "spatial-temporal" dual dimension, directly modeling the dynamic association between adjacent and non-adjacent frames through block-wise attention computation (such as Tubelet Attention and Spatio-Temporal Attention) on video frame sequences, avoiding misidentification of dynamic topics caused by isolated single-frame processing, and significantly improving the accuracy of action topic recognition on datasets such as Kinetics [13]. The Visual Attention-Guided Prompt model designed by scholars from Tsinghua University [14] (mentioned in the original document) uses attention mechanisms to locate key visual regions in videos (such as "guitar" and "hat" in "a street performer playing music"), and embeds these features into local text prompts (such as generating a dynamic prompt of "concert featuring guitar and outdoor scenes"), achieving precise binding between text semantics and video details. The hierarchical temporal evolution modeling proposed by Pasad et al. in self-supervised speech model analysis quantifies the temporal correlation of features at different levels (such as capturing inter-frame motion at lower levels and event evolution at higher levels), providing an interpretable basis for the dynamic evolution of video topics. Similar ideas applied to the video domain can distinguish between "marathon" (long-term coherent events) and "track and field competition" (short-term isolated events) [15][16].

Inspired by the feature pyramid theory in computer vision [17] and the gated fusion mechanism in natural language processing, this paper proposes a Multi-scale Temporal-aware Prompt Learning (MTPL) framework.

In general, the main contributions of this paper are as follows:

- Propose the Cross-Frame Communication Transformer (Cross-Frame Communication Transformer (CFCT)), which models the dynamic dependencies between video frames through inter-frame attention mechanisms and message passing.
- Design a dynamic prompt generator (Video-Specific Prompt Generator (VSP)) that optimizes text prompts adaptively based on multi-scale visual features of videos, alleviating cross-modal semantic misalignment.
- Construct a multi-scale Local Feature Extractor (MLFE) that integrates features of different scales through an FPN structure, covering both global scenes and local key cues.

achieved through multiple layers of blocks. The temporal attention layer precedes the Transformer block and is specifically designed to capture the temporal dependencies between video frames. Through the self-attention mechanism, it enables the model to focus on the associations between different frames, thereby better understanding the temporal information of the video. The two Transformer layers are respectively used for cross-frame fusion attention and intra-frame diffusion attention.

$$x_t = \text{LN}(x_t) + \text{DropPath}(\text{MHA}(\text{LN}(x_t))) \quad (1)$$

$$\text{msg_token} = \text{Linear}(x[0, :, :, :]) \quad (2)$$

$$\text{msg_token} = \text{msg_token} + \text{DropPath}(\text{MHA}(\text{LN}(\text{msg_token}))) \quad (3)$$

The message tokens form a separate communication pathway that operates orthogonally to the standard self-attention in Transformer blocks. This design enables long-range temporal dependencies without the quadratic complexity of full spatio-temporal attention.

$$x = \text{concat}(x, \text{msg_token}) \quad (4)$$

Among them, MHA stands for Multi-Head Attention mechanism, LN for Layer Normalization, and DropPath for Random Dropout Regularization.

Specifically, given a video clip $V \in \mathbb{R}^{T \times H \times W \times 3}$ with T sampled frames, where H and W represent spatial resolutions, the T -th frame is divided into N non-overlapping patches $\{x_{t,i}\}_{i=1}^N$, each with a size of $P \times P$ pixels, where $t \in \{1, \dots, T\}$ represents the temporal index, and $N = HW/P^2$. Then these patches $\{x_{t,i}\}_{i=1}^N$ are embedded into patch embeddings. Afterwards, we add a learnable embedding x_{class} to the sequence of embedded patch embeddings, called the [class] token. Its state at the encoder output serves as the frame representation. The input to the cross-frame communication transformer at frame t is denoted as

$$z_t^{(0)} = [x_{\text{class}}, Ex_{t,1}, Ex_{t,2}, \dots, Ex_{t,N}] + e^{\text{spa}} \quad (5)$$

Here, e^{spa} represents spatial position encoding. Then, tokens from the same spatial position across different frames form a sequence, and attention aggregation is performed along the temporal dimension to capture inter-frame motion or temporal dependencies.

$$A = \text{Softmax}\left(\frac{(XW_Q)(XW_K)^T}{\sqrt{d_k}}\right) \quad (6)$$

Here, X is the input sequence, W_Q and W_K are learnable projection matrices, and d_k is the scaling factor.

A linear transformation is then applied to convert the frame-level X_{class} into message tokens. All message tokens are jointly learned and computed using a cross-attention mechanism. In this process, each message token serves as the query, while all other message tokens serve as the keys and values. This learns the global spatio-temporal

dependencies of the video, enabling information exchange between frames and capturing the temporal relationships within the video.

$$\mathbf{M}_{\text{new}} = \text{LayerNorm}(\mathbf{M} + \text{Softmax}(\frac{(\mathbf{X}\mathbf{W}^Q)(\mathbf{W}^K)^T\mathbf{M}^T}{\sqrt{d_k}}))(\mathbf{M}\mathbf{W}^V) \quad (7)$$

where $\mathbf{M} \in \mathbb{R}^{T \times d}$ is the matrix of message tokens from all frames, $\mathbf{W}^Q, \mathbf{W}^K, \mathbf{W}^V \in \mathbb{R}^{d \times d}$ are learnable projection matrices for queries, keys, and values respectively, and d_k is the dimension of keys. Finally, the frame tokens and corresponding message tokens are concatenated, and through the message tokens, global spatio-temporal dependencies are transmitted to the tokens of the current frame, thereby enabling information diffusion within the frame.

A single Block module can only perform one cross-frame information exchange. Multiple Block modules can exchange information multiple times, thereby accumulating more temporal information and modeling the dependencies between video frames more comprehensively. The output of the last Block module is the visual representation $\mathbf{h}_t$ of the frame.

2.2 MultiframeIntegrationTransformer

The module is responsible for integrating the features of all frames to form a video-level feature representation. It takes all frame representations $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_T]$ as input and outputs the video-level representation $\mathbf{v}$ as follows. Specifically, this module employs a standard multi-head self-attention mechanism to learn the dependencies between frame-level feature representations. This attention mechanism can capture the spatio-temporal relationships between video frames, such as motion continuity or scene changes between adjacent frames. After being processed by the attention mechanism, each frame-level feature representation is fed into a feed-forward network for non-linear transformation, further enhancing the expressive power of the features. Finally, all frame-level feature representations are averaged through average pooling to obtain a global video-level feature representation. This feature representation contains the overall semantic information of the video.

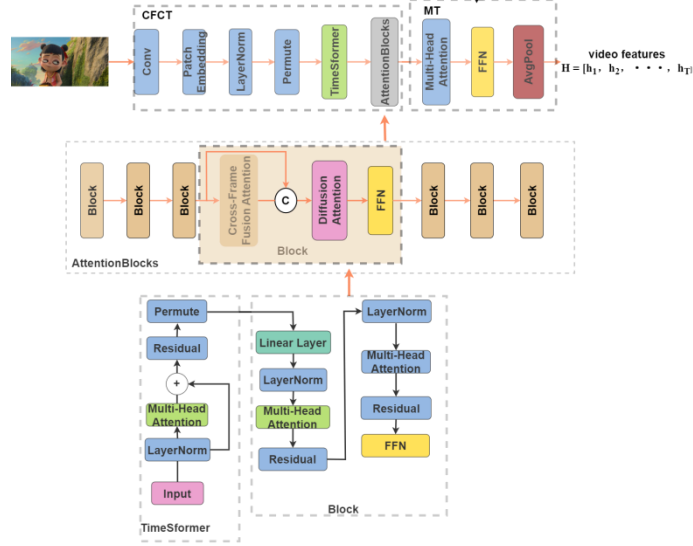


Fig. 2. CFCT And MT.

2.3 Multi-scale Local Feature Extractor

We designed a specific multi-scale feature extraction module. The MLFE module is implemented based on the FPN architecture, with a multi-scale quantity `num_scales` of 3, corresponding to downsampling factors of 1, 2, and 4; the number of local regions `local_regions` is 4, generated through a region projection layer; a 3×3 convolution kernel is used for feature fusion, with padding of 1; each scale of horizontal connections uses a 1×1 convolution to adjust the channel dimension. This module first performs bottom-up feature extraction, i.e., extracting features layer by layer from video frames. These feature maps are propagated through layers in a convolutional neural network (CNN), with each layer containing feature information at different scales and hierarchical levels. During this process, the resolution of the feature maps gradually decreases while the semantic information gradually becomes richer. Each layer of feature maps represents an abstract representation of the input image at different scales.

$$C_i = \text{AdaptivePool}\left(X, \frac{1}{2^i}\right)$$

$$= \begin{cases} \text{AvgPool}_{2^i}(X) & \text{if } H \geq 2^i \text{ and } W \geq 2^i \\ \text{AdaptivePool}_{(1,1)}(X) & \text{otherwise} \end{cases} \quad (8)$$

where the input feature $X \in \mathbb{R}^{B \times T \times H \times W \times C}$, with B being the batch size, T the number of time steps, H and W the spatial dimensions, and C the number of channels.

Afterwards, we perform top-down feature fusion. High-level feature maps are first upsampled (e.g., using bilinear interpolation, deconvolution, etc.) to match the resolution of the feature maps from the lower layer. Then, the upsampled high-level feature maps are fused with the corresponding low-level feature maps. During the fusion process, to maintain consistent channel dimensions, a 1×1 convolution operation is applied to the low-level feature maps to reduce their channel count.

$$P_i = \text{Conv}_{3 \times 3}(\text{ReLU}(L_i + \text{Upsample}(P_{i+1}))) \quad (9)$$

Subsequently, the top-down feature fusion path and the bottom-up feature extraction path are connected through lateral connections. These lateral connections combine the high-resolution information from low-level feature maps with the rich semantic information from high-level feature maps, forming new feature maps.

$$L_i = \text{Conv}_{1 \times 1}(C_i) = W_{\text{lateral}}^i \cdot C_i + b_{\text{lateral}}^i \quad (10)$$

where $W_{\text{lateral}}^i \in \mathbb{R}^{C \times C}$ is the convolutional weight matrix.

Through the above steps, a feature pyramid is constructed. This pyramid contains feature maps of multiple scales from the bottom layer to the top layer, and each feature map integrates feature information from different hierarchical levels.

Global average pooling is performed on each pyramid layer to generate multi-scale local features.

$$F_i = \text{GlobalAvgPool}(\text{reshape}(P_i, [B, T, C, H_i, W_i])) \quad (11)$$

where H_i and W_i are the spatial dimensions of the i -th layer features. Finally, we obtain the multi-scale local feature set $L = \{L_0, L_1, L_2, \dots, L_{N-1}\}$. Our semantic-guided weighting mechanism extends beyond standard cross-modal attention by introducing a hierarchical scale-aware fusion strategy. Unlike conventional dot-product attention that treats all spatial regions equally, our method first computes scale-specific semantic relevance through a multi-head gating mechanism:

$$G_b = \text{MultiHead}(q_b, \{V_{b,s}\}_{s=1}^S) \quad (12)$$

where S is the number of scales, and $G_b \in \mathbb{R}^{S \times H \times W}$ denotes scale-aware attention weights. This enables the model to dynamically determine which scales are most relevant for each semantic concept, addressing the limitation of fixed-scale feature fusion in standard FPN architectures. Specifically, first, the input text features are converted into a global text query vector, serving as a semantic guidance signal.

$$q_b = \frac{1}{L} \sum_{i=1}^L T_{b,i} \in \mathbb{R}^D \quad (13)$$

Here, $T \in \mathbb{R}^{B \times L \times D}$ is the text feature sequence, where $b \in \mathbb{R}^{B \times 1 \times D}$ represents the batch index, expanded to text feature q as the query vector.

Semantic similarity computation is performed: for visual features $V \in \mathbb{R}^{B \times T \times H \times W \times D}$, the dot-product similarity between each spatial position and the text query is calculated.

$$S_{b,t,h,w} = \sum_{d=1}^D V_{b,t,h,w,d} \cdot q_{b,d} \quad (14)$$

where $S \in \mathbb{R}^{B \times T \times H \times W}$ is the unnormalized similarity map.

Apply the softmax function to the spatial dimensions of each time frame to obtain normalized regional weights.

$$W_{b,t,h,w} = \frac{\exp(S_{b,t,h,w})}{\sum_{h'=1}^H \sum_{w'=1}^W \exp(S_{b,t,h,w})} \quad (15)$$

where $W \in \mathbb{R}^{B \times T \times H \times W}$ and satisfies $\sum_{h,w} W_{b,t,h,w} = 1$ for each b,t . Afterwards, the generated regional weights are used to perform weighted fusion of multi-scale local features. The weighted local features are fused with global features through a cross-attention mechanism, which enables the model to dynamically adjust its attention to different spatial regions.

2.4 Video-Specific Prompt Generator (VSP)

Generating a good textual description for each video is a challenging problem. The key idea of our method is to use video content to enhance textual representations. Previous works typically manually define text prompts, such as "A photo of a {label}". However, such manually designed prompts fail to improve video recognition performance. In contrast, we simply use "{label}" as the textual description and then propose a learnable text prompting scheme.

The VideoSpecificPrompt (VSP) is the core component of the MTPL model, responsible for implementing progressive fusion of local-global features and textual semantic enhancement. This module adopts a multi-layer decoding architecture, with each layer containing four key computational units that achieve precise alignment between visual features of different granularities and textual semantics through a hierarchical processing mechanism.

Specifically, we employ a multi-layer bidirectional cross-attention mechanism guided by text. The core objective is to enable deep bidirectional information interaction between textual features and multi-scale video features (both global and local), thereby generating dynamic prompts that are highly relevant to the video content. This allows the global features from the video encoder and the local features from the feature pyramid to guide and enhance each other. The global features of a video (e.g., "sports") are high-level abstractions, but they require specific local details (e.g., "shooting action") for support. This step allows the global features to act as the "questioner" that "seeks answers" from the local features. By using global features to guide local features, we treat the global features as queries (Query) and the local features as keys and

values (Key & Value). This enables the model to select which local details are important based on the global context.

$$\text{global_guided_local} = \text{CrossAttention}\left(\begin{matrix} \text{global_as_query} \\ \text{local_as_kv} \\ \text{local_as_kv} \end{matrix}\right) \quad (16)$$

Here, global_as_query compresses global visual features into sequence features through average pooling, while local_as_kv fuses the multi-scale local feature list into a unified local feature representation. The attention score is

$$\text{Attention}(Q_g, K_1, V_1) = \text{Softmax}\left(\frac{Q_g K_1^T}{\sqrt{d_k}}\right) V_1 \quad (17)$$

This enables the model to weight and aggregate local, detailed features based on global context. Conversely, local details may also contain key information that has not been captured by global features. This step allows local features to act as the "questioner" to supplement and correct global features, thus using local to guide global by treating local features as queries and global features as keys and values. This enables global features to be enhanced by those discriminative local details. This process allows each local region to obtain supplementary information from global features according to its own needs.

The above two features are concatenated to obtain visual context features, forming rich visual context. Next, cross-attention fusion is performed with text features. This enables the text features to actively extract the most relevant content from the video information. At the same time, global average pooling is applied to the visual context to obtain a global visual summary, which is then expanded to match the length of the text sequence. The features enhanced by cross-attention and the original text features are dynamically balanced through a learnable gating mechanism that weights the contributions of the original text, visually-enhanced text, and global visual features. The network learns a weight that dynamically determines to what extent the original text information should be preserved and to what extent information extracted from the video should be incorporated in the final output. This adaptive mechanism ensures the flexibility of the fusion.

Then, residual connections are applied to alleviate the vanishing gradient problem in deep networks. Processed through MLP, MLP provides nonlinear transformation capability. Further integrate information to generate adaptive prompts that deeply fuse video spatio-temporal information, significantly enhancing video-text alignment capabilities, and generate the final video-conditioned prompt (Prompt).

Finally, through contrastive learning, the model learns to align video features and text features. Specifically, the video features and their corresponding text features are treated as positive samples, while video features paired with random text features are treated as negative samples. The model is optimized through a loss function, and finally, the category with the highest similarity is selected as the theme of the video.

3 EXPERIMENTS

3.1 Datasets

To ensure the accuracy and reliability of the research, extensive data investigation and examination work was conducted. In our experiment, we used the following two datasets: Kinetics-400 and Kinetics-600. Kinetics-400 and Kinetics-600 are two large datasets that include 400 and 600 categories respectively. Each dataset consists of video clips extracted from YouTube videos, with an average duration of 10 seconds. The Kinetics-600 dataset enhances the Kinetics-400 dataset by merging an additional 220 categories. Additionally, to evaluate the model's performance on more focused topic recognition tasks, we created two reorganized datasets from the original Kinetics datasets. For Kinetics-400-R20, we mapped the 400 original categories into 20 semantically coherent super-categories (e.g., "Art and Creation", "Medical Care and Nursing", "Cooking and Dining", "Military and Police Actions"). Similarly, for Kinetics-600-R30, we mapped the 600 original categories into 30 semantically coherent super-categories following the same principle. Critically, no training, validation, or testing samples were removed or added during this reorganization process—all original samples were preserved with their labels remapped to the corresponding super-categories. This approach maintains the exact same sample distribution as the full datasets while reducing classification complexity and creating more focused topic recognition scenarios that better evaluate fine-grained local feature perception capabilities. The original training, validation, and testing splits were preserved for these subsets, maintaining the same sample distribution as the full datasets while reducing the classification complexity. This experimental design allows us to specifically assess the model's capability in fine-grained topic recognition scenarios where local feature perception is critical.

Table 1. Statistics of the datasets.

datasets	Train	Val	Test
Kinetics-400	240,436	19,796	19906
Kinetics-600	383,393	27,910	59982

3.2 Implement details

The model is implemented based on the PyTorch framework and trained and tested on systems equipped with NVIDIA GPUs. The model architecture consists of the following core components: (1) Cross-frame Communication Transformer (CFCT) adopts ViT-L/14 as the base architecture, introducing the proposed cross-frame attention mechanism that effectively models temporal dependencies between video frames through a message token mechanism; (2) Multi-frame Integration Transformer (MT) contains 1 layer of standard multi-head self-attention mechanism and feed-forward network, responsible for aggregating frame-level features from CFCT into video-level

representations; (3) Text Encoder integrates the CLIP pre-trained text encoder, providing strong text semantic understanding capabilities; (4) Video-specific Prompting Module employs 2 layers of multi-head self-attention mechanism and feed-forward network, dynamically generating more discriminative text prompts based on video content and text representations, with initial text descriptions formatted as {label}; (5) Multi-scale local feature extractor adopts FPN (Feature Pyramid Network) architecture, utilizing 3 scales and 4 local regions for text-guided feature extraction. The training process employs the AdamW optimizer with betas parameter set to (0.9, 0.98) and weight decay fixed at 0.001. Learning rate scheduling uses cosine annealing strategy with a 5-epoch linear warmup phase. The base learning rate is set to 8×10^{-6} . Data augmentation strategies include random horizontal flipping, multi-scale cropping, color jittering, grayscale conversion, as well as regularization techniques such as label smoothing, Mixup, and Cutmix. The model uses learnable absolute position encoding to process spatio-temporal information. During inference, differentiated sampling and evaluation strategies are adopted: sparse sampling selects 8 or 16 frames with a multi-view inference strategy using 3 spatial crops and 4 temporal segments; model performance is evaluated using the best checkpoint selected based on the validation set. For the subset experiments (20-class Kinetics-400 and 30-class Kinetics-600), we maintained identical training hyperparameters as the full-dataset experiments. The only modification was the classifier layer dimension to match the reduced number of categories. All other architectural components, including the Cross-Frame Communication Transformer, Multi-scale Local Feature Extractor, and Video-Specific Prompt Generator remained unchanged to ensure fair comparison and validate the general applicability of our approach across different classification granularities.

Table 2. Ablation study

METHOD	TOP1	TOP5
BaseLine	88.3	97.7
CFCT+BaseLine	89.9	98.3
VSP+BaseLine	89.1	98.2
MLFE+BaseLine	89.0	98.0
CFCT+MLFE+VSP+BaseLine	92.0	98.5

The results from the kinetics600 experiment indicate that each component can independently enhance the model's performance. The CFCT module, by modeling the temporal dependencies between video frames, has improved the Top-1 accuracy by 1.6 percentage points; the MLFE module effectively enhances the model's understanding of fine-grained actions by capturing multi-scale local semantic features. Notably, when the three modules work together, the model achieves optimal performance with a Top-1 accuracy of 92.0%, which is 3.7 percentage points higher than the baseline model, fully demonstrating the complementarity between the components. In particular, our complete model significantly improves Top-1 accuracy while maintaining high Top-5 accuracy, indicating stronger discriminative capability in complex action recognition tasks. Additionally, the ablation experiments reveal the importance of

temporal modeling, multi-scale feature extraction, and vision-language interaction in video understanding tasks, providing valuable reference for future research.

3.3 Comparison with the State-of-the-Art

We employ a sparse sampling method to sample 8 or 16 frames. The results, as presented in **Table 3** and **Table 4**, demonstrate the effectiveness of the proposed method. The MTPL model exhibits significant advantages on both the Kinetics400 and Kinetics600 datasets. On Kinetics400, it achieves the highest Top1 accuracy of 88.6% and Top5 accuracy of 97.8%, fully demonstrating its superior performance. On Kinetics600, it leads all comparative methods with a Top1 accuracy of 92.0% and Top5 accuracy of 98.5%, with the Top1 accuracy being 2.5 percentage points higher than the second-best model. This model achieves optimal results with only 8 frames of input, significantly improving inference efficiency compared to high-performance models such as Swin-B, MViTv2-B, and M²-CLIP, which require 32 frames. As a model pre-trained on CLIP-400M, MTPL performs optimally among all CLIP-based methods, achieving a Top1 accuracy 1.3 percentage points higher than the second-best X-CLIP-L/14 model, reflecting the efficient utilization of pre-trained knowledge. Despite its high computational complexity, its excellent balance between accuracy and frame efficiency makes it an ideal choice for high-precision video understanding tasks.

Table 3. Performance comparison on Kinetics400 dataset

METHOD	Pretain	Tunable Param	Top1	Top5
Swin-B	IN-21k	88	82.7	95.5
MViTv2-B	-	52	82.9	95.7
Uniformer V2-B/16	CLIP-400M	115	85.6	97.0
S-ViT-B/16	CLIP-400M	-	84.7	96.8
Vita-CLIP-B/16	CLIP-400M	39	82.9	96.3
M2-CLIP-B/16	CLIP-400M	16	85.4	96.1
X-CLIP-B/16	CLIP-400M	132	87.1	97.6
MTPL	CLIP-400M	143	88.6	97.7

Table 4. Performance comparison on Kinetics600 dataset

	Pretain	Frames	Top1	Top5	Views
Swin-L	IN-21k	32	86.1	97.3	10×5
MViTv2-L	IN-21k	32	87.9	97.9	4×3
MoViNet-A6	-	32	84.8	96.5	1×1
ViT-L-ViViT	IN-21k	32	83.0	95.7	4×3
MTV-H	JFT-300M	32	89.6	98.3	4×3
TimeSformer-L	IN-21k	32	82.2	95.6	3×1
X-CLIP-L/14	CLIP-400M	8	88.3	97.7	4×3
MTPL	CLIP-400M	8	90.2	98.1	4×3

To specifically evaluate our model's performance on focused topic recognition tasks, we conducted additional experiments on the 20-class Kinetics-400 subset and 30-class Kinetics-600 subset. These subsets represent scenarios where fine-grained local perception is particularly crucial, such as distinguishing between similar laboratory procedures or different cooking techniques.

Table 5. Performance comparison on subset datasets

	Kinetics-400-R20		Kinetics-600-R30	
	Top1	Top5	Top1	Top5
ViT-L-ViViT	93.0	98.7	83.1	98.8
X-CLIP-L/14	93.4	99.3	93.9	99.5
TimeSformer-L	92.1	98.9	85.2	98.4
Ours	93.9	99.4	95.5	99.8

As shown in **Table 5**, our MTPL model achieves significant performance gains on both subset datasets, with Top-1 accuracy improvements of 0.7% and 1.6% over the second-best method on Kinetics-400-R20 and Kinetics-600-R30 respectively. This substantial improvement demonstrates that our multi-scale local perception mechanism is particularly effective for fine-grained topic recognition tasks where subtle local details (e.g., "test tubes" in laboratory scenes) are critical discriminative features. The results validate our hypothesis that semantic-guided multi-scale feature extraction is essential for accurate video topic recognition, especially in scenarios requiring detailed local perception.

4 CONCLUSION

This study successfully demonstrates the effectiveness of the proposed method in addressing the identified research problem across various classification granularities. Our experiments on both full datasets (Kinetics-400, Kinetics-600) and focused subsets (20-class and 30-class) confirm that the multi-scale local perception mechanism is particularly crucial for fine-grained topic recognition tasks. The significant performance improvement on subset datasets (93.9% and 95.5% Top-1 accuracy) validates our approach's effectiveness in scenarios requiring detailed local feature extraction, such as distinguishing between subtle visual cues in "laboratory," "medical surgery," and "cooking process" scenes. The experimental results confirm our hypothesis through multiple evaluation metrics, with our framework consistently outperforming existing methods across different dataset configurations. The main contributions include a novel architecture integrating Cross-Frame Communication Transformer, Multi-scale Local Feature Extractor, and Video-Specific Prompt Generator, which together provide a comprehensive solution for semantic-guided video topic recognition. These findings significantly enhance our understanding of multi-scale feature integration in video understanding tasks and provide practical implications for real-world applications in intelligent surveillance, content retrieval, and recommendation systems where fine-grained topic recognition is essential.

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References

- [1] Y. Wang, Y. Xu, Y. Yang, et al., "InternVid: A large-scale video-text dataset for multi-modal understanding and generation," in *Int. Conf. Learn. Represent. (ICLR)*, 2024.
- [2] L. Wang, Z. Qiao, S. Tang, et al., "Temporal segment networks: Towards good practices for deep action recognition," in *Eur. Conf. Comput. Vis. (ECCV)*, 2016, pp. 20–36.
- [3] M. Bain, A. Nagrani, G. Varol, and A. Zisserman, "Frozen in time: A joint video and image encoder for end-to-end retrieval," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV)*, 2021, pp. 1764–1774.
- [4] T.-Y. Lin, P. Dollár, R. Girshick, et al., "Feature pyramid networks for object detection," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2017, pp. 2117–2125.
- [5] C. Feichtenhofer, H. Fan, J. Malik, and K. He, "SlowFast networks for video recognition," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, 2019, pp. 6202–6211.
- [6] A. Radford, J. W. Kim, C. Hallacy, et al., "Learning transferable visual models from natural language supervision," in *Proc. Int. Conf. Mach. Learn. (ICML)*, 2021, pp. 8748–8763.
- [7] K. Zhou, J. Yang, C. C. Loy, and Z. Liu, "Learning to prompt for vision-language models," *Int. J. Comput. Vis. (IJCV)*, vol. 131, no. 9, pp. 2337–2358, 2023.
- [8] C.-Y. Lin, Y. Zhu, W. Wang, and J. Cai, "MVITv2: Improved multiscale vision transformers for classification and detection," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2022, pp. 3021–3031.
- [9] Y. Li, H. Fan, R. Gupta, et al., "UniFormer: Unified transformer for efficient spatiotemporal representation learning," in *Int. Conf. Learn. Represent. (ICLR)*, 2022.
- [10] J. Liu, B. Chen, Y. Wang, et al., "MERU: Multimodal entity retrieval and understanding for video topic recognition," *IEEE Trans. Pattern Anal. Mach. Intell. (TPAMI)*, vol. 46, no. 5, pp. 2876–2891, 2024.
- Yang, Yunfan, et al. "Guided shuffled frog-leaping algorithm for flexible job shop scheduling problem with variable sublots and overlapping in operations." *Computers & Industrial Engineering* 180 (2023): 109209.
- [11] G. Bertasius, H. Wang, and L. Torresani, "Is space-time attention all you need for video understanding?" in *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2021.
- [12] A. Vaswani, N. Shazeer, N. Parmar, et al., "Attention is all you need," in *Adv. Neural Inf. Process. Syst. (NeurIPS)*, 2017, pp. 5998–6008.
- [13] J. Carreira and A. Zisserman, "Quo vadis, action recognition? A new model and the kinetics dataset," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2017, pp. 6329–6338.
- [14] D. Li, J. Li, H. Li, et al., "Align and prompt: Video-and-language pre-training with entity prompts," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2022, pp. 17632–1764.
- [15] Z. Tong, Y. Wang, Z. Wang, et al., "VideoMAE: Masked autoencoders are data-efficient learners for self-supervised video pre-training," in *Adv. Neural Inf. Process. Syst. (NeurIPS)*, 2022, pp. 15884–15996.
- [16] S. Sun, Y. Zhang, L. Wang, et al., "X-CLIP: End-to-end multi-grained contrastive learning for video-text retrieval," in *Proc. ACM Int. Conf. Multimedia (ACM MM)*, 2022, pp. 5354–536.