Method and Analysis of Violent Behavior Recognition Based on Multimodal Information Fusion

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Abstract. This article provides a systematic review and analysis of methods for identifying violent behavior based on multimodal information fusion. The research focuses on two main themes: "Feature Extraction Network - Multimodal Fusion Strategy". In a unified experimental framework, the article compared the differences in parameter quantity, computational efficiency, and detection accuracy among 3D CNN, ConvLSTM, GhostNet, and other networks, and analyzed the performance of early fusion, late fusion, and attention fusion strategies on public datasets such as RWF-2000. By quantitatively comparing the interaction between feature extraction networks and fusion strategies, this study aims to fill in the current review that lacks engineering implementation guidance. Research has found that existing reviews often focus on a single technological path, or only list network structures, or compare fusion strategies, lacking a systematic induction of the "network fusion" coupling effect within the same framework. This makes it difficult for researchers to make quick decisions based on computing power, real-time performance, and privacy constraints during actual deployment. This article provides a reference for researchers to choose appropriate feature extraction networks and fusion strategies in practical applications by analyzing several representative works in a unified coordinate system.

Keywords: Identification of violent behavior, Multimodal fusion, Feature extraction network, Integration strategy.

1. Introduction

As social security issues become increasingly prominent, the automatic identification and early warning of violent behavior have emerged as critical research topics in the field of public safety. Traditional violent behavior recognition primarily relies on single-modal information (such as visual or audio), facing issues like insufficient accuracy and weak generalization capabilities. Multimodal information fusion integrates data from multiple sources such as video, audio, and sensors to capture the characteristic manifestations of violent behavior from different dimensions, significantly enhancing recognition accuracy and robustness. This study provides a systematic review and analysis of violent behavior recognition methods based on multimodal information fusion, centered on two main themes — “Feature Extraction Networks” and “Multimodal Fusion Strategies” — aimed at providing researchers with a clear technical roadmap and practical engineering implementation guidance. The primary objective of this study is to advance the widespread implementation of violent behavior recognition technology in fields such as public security, campus protection, and the development of smart urban centers.

This study aims to systematically analyze and compare violent behavior recognition methods based on multimodal information fusion, thereby bridging the gap between theory and practice in existing research. This technological gap has severely impacted the efficiency of public safety management. A limitation of existing research is that reviews often discuss feature extraction networks or fusion strategies in isolation. They lack a systematic evaluation of the synergistic effects between these components. Different studies employ varying experimental settings and evaluation criteria, making it difficult to compare results across studies; Insufficient guidance on project implementation also fails to provide clear technical selection criteria for practical application scenarios.

To address these issues, the article establishes a unified evaluation framework. Within this framework, we empirically benchmark representative models employing a unified approach. The study focuses on evaluating the combined effects of feature extraction networks such as 3D CNN, ConvLSTM, and GhostNet with different fusion strategies. The purpose of this research is to provide practical technical selection guidelines for security system engineers and algorithm researchers. This capability facilitates the selection of the most appropriate network architecture and fusion methods in accordance with specific constraints, including computational capacity, real-time performance criteria, and data privacy considerations.

2. Fundamentals of Violent Behavior Recognition and Multimodal Information Acquisition

2.1. Fundamental Concepts of Violent Behavior Recognition

Violent behavior recognition refers to the process of automatically detecting and identifying human violent actions through technologies such as computer vision and audio analysis. According to the World Health Organization's definition, violence is “the intentional use of physical force or power, threatened or actual, against oneself, another person, or against a group or community, that either results in or has a high likelihood of resulting in injury, death, psychological harm, maldevelopment, or deprivation [1].

2.2. Multimodal Information Acquisition Technology

2.2.1. Visual Information Acquisition

Visual information is the most commonly used modality for identifying violent behavior, primarily collected through video sequences captured by camera equipment. Visual information acquisition devices primarily include standard RGB cameras, infrared cameras, depth cameras, and similar equipment. RGB cameras capture two-dimensional image sequences in the visible light spectrum. Current mainstream surveillance cameras achieve resolutions up to 4K (3840×2160) with frame rates ranging from 25 to 60 frames per second. Depth cameras can simultaneously capture RGB images and depth information, using structured light or ToF (Time of Flight) technology to obtain the three-dimensional structure of a scene [2, 3].

2.2.2. Audio Information Acquisition

Audio information serves as a vital complement to visuals, providing acoustic clues such as screams and combat sounds in violent scenes. Audio capture devices primarily include monaural microphones, stereo microphones, and microphone arrays. In violent behavior recognition, the commonly used audio sampling rate is 16 kHz or 44.1 kHz, with a bit depth of 16 bits. In environments with high ambient noise levels, microphone arrays can effectively enhance the signal-to-noise ratio through beamforming technology, enabling directional capture of audio information from key areas. In audio feature extraction, the primary components include time-domain features (zero-crossing rate, short-term energy) and frequency-domain features (MFCC, Mel-spectrogram).

2.2.3. Sensor Data Acquisition

Sensor data acquisition provides supplementary information beyond audiovisual channels for violent behavior recognition. Common sensor types include: inertial sensors (e.g., accelerometers and gyroscopes), which capture the acceleration and angular velocity characteristics of human motion, typically at sampling rates of 50–200 Hz; pressure sensors, which detect pressure changes caused by actions such as striking or kicking; and biosensors (e.g., devices for monitoring physiological parameters like heart rate and skin conductance), which can assist in identifying states of emotional arousal.

3. Network Analysis of Feature Extraction for Violent Behavior Recognition

3.1. 3D CNN Model Based on Spatiotemporal Features

3.1.1. 3D Convolutional Neural Network Architecture

3D CNNs are a natural extension of traditional 2D CNNs in deep learning architecture, specifically designed to process three-dimensional data such as video. 3D CNNs can perform convolutional operations simultaneously in both temporal and spatial dimensions, thereby capturing spatio-temporal features within video sequences.

A typical 3D CNN architecture primarily consists of multiple 3D convolutional layers, pooling layers, batch normalization layers, and fully connected layers. For example, the C3D architecture employs 8 convolutional layers, 5 max-pooling layers, and 2 fully-connected layers, processing inputs of 16 consecutive frames. I3D (Inflated 3D ConvNet) is another significant variant of 3D CNNs. It achieves more efficient parameter utilization by "inflating" the parameters of a pre-trained 2D CNN model [4].

3.1.2. 3D Convolutional Neural Network Applications

3D CNNs have found extensive application in violent behavior recognition due to their powerful spatio-temporal feature extraction capabilities. Multiple studies employ pre-trained I3D models as video feature extractors. For example, researchers employed an improved I3D network on the RWF-2000 dataset. They split each video into segments of fixed length. By extracting spatio-temporal features from each segment and then performing temporal integration, they achieved an accuracy of 93.6% [5].

3.1.3. Performance and Efficiency Analysis

In terms of recognition performance, 3D CNNs demonstrate outstanding performance on mainstream violent behavior datasets: On the RWF-2000 dataset, the I3D variant achieved an average accuracy of 93.2%, while the C3D variant reached 89.5%; On the Hockey Fight dataset, the average accuracy rates were 95.6% and 92.8%, respectively. Particularly for violent acts involving complex spatiotemporal relationships (e.g., kicking, punching, shoving), 3D CNN outperforms 2D CNN models by 4 to 7 percentage points.

The high performance comes with significant computational overhead. The standard C3D model has approximately 78 million parameters, while I3D has about 25 million. Both require substantial GPU resources during the training phase. Using the NVIDIA Tesla V100 as an example, training a brute-force recognition model based on 3D CNNs typically takes 24 to 48 hours. During the inference phase, processing a 5-second 720p video takes approximately 0.85 seconds for C3D and 0.53 seconds for I3D, posing challenges for real-time applications [4].

Overall, 3D CNNs demonstrate high accuracy but are computationally intensive in violent behavior recognition, making them suitable for scenarios demanding high precision and ample computational resources. In resource-constrained environments, appropriate optimization strategies must be adopted.

3.2. ConvLSTM Network with Integrated Temporal Information

3.2.1. ConvLSTM Network Architecture

ConvLSTM (Convolutional Long Short-Term Memory) networks are a type of neural network architecture specifically designed to process spatiotemporal sequence data. It ingeniously integrates convolutional operations into the LSTM architecture, enabling the network to simultaneously capture spatial features and temporal dependencies.

3.2.2. Application of ConvLSTM in Violent Behavior Recognition

In recent years, the application of ConvLSTM in the field of violent behavior recognition has significantly increased. According to a study published in Pattern Recognition Letters in 2021, researchers applied ConvLSTM to detect violent behavior in surveillance videos. By extracting

optical flow information between consecutive frames and feeding it into the ConvLSTM network, they successfully captured the unique spatio-temporal movement patterns characteristic of violent actions. This method achieved an accuracy of 94.8% on the Hockey Fight dataset.

Regarding multimodal fusion, researchers proposed integrating ConvLSTM with an audio feature network to construct a dual-stream network architecture. Video streams extract spatio-temporal features via ConvLSTM, while audio streams extract audio features through 1D-CNN. Subsequently, these features are fused using an attention mechanism. This method achieved a recognition rate of 92.6% on the RWF-2000 dataset, representing a 4.3% improvement over single-modality approaches [6].

3.2.3. Performance and Efficiency Analysis

Experiments on the RWF-2000 dataset demonstrate that, compared to traditional 3D CNNs, the ConvLSTM model reduces the number of parameters by approximately 35% and shortens the single-pass inference time by 28%. This makes it more suitable for resource-constrained edge device deployments.

Performance gains come at a cost. The latest research data indicates that ConvLSTM exhibits training instability when processing long sequences (>128 frames), and its GPU memory consumption increases linearly with sequence length. When training on an RTX 2080 Ti with a batch size of 16, processing a 64-frame sequence requires approximately 11GB of VRAM [5].

3.3. Lightweight GhostNet Network

3.3.1. GhostNet Network Architecture

GhostNet is a lightweight convolutional neural network architecture proposed by Huawei Noah's Ark Lab in 2020, designed specifically to address the resource constraints of mobile devices. Its core innovation lies in introducing the concept of the “Ghost module”. This module leverages the inherent redundancy in feature maps to generate “ghost feature maps” using fewer convolutional kernels, thereby significantly reducing the number of network parameters and computational overhead.

The operation of the Ghost module involves the following steps: First, use standard convolutions to generate a small number of basic feature maps. Then, through a series of linear transformations (such as depthwise convolutions, 1×1 convolutions, and other low-cost operations), these basic feature maps are transformed to generate more feature representations.

3.3.2. Application of GhostNet in Violent Behavior Recognition

In multimodal violent behavior recognition, GhostNet is frequently employed to process visual information streams. Researchers proposed a violent behavior recognition framework based on GhostNet, applying GhostNet to video frame feature extraction and integrating it with audio features. This method achieved an accuracy of 92.7% on the RWF-2000 dataset, while the model size is only about one-quarter that of the traditional ResNet50.

3.3.3. Performance and Efficiency Analysis

In violent behavior recognition tasks, GhostNet demonstrates an excellent balance between performance and efficiency.

Comparative experiments on the RWF-2000 dataset demonstrate that, Methods based on GhostNet achieved accuracy levels ranging from 91.8% to 93.5%, comparable to those using ResNet50 (92.6%–94.3%), while requiring only about 22% of the model parameters. In terms of computational efficiency, GhostNet achieves approximately 18% of ResNet50's FLOPs. This enables GhostNet-based systems to process at around 34 frames per second on an Intel Core i5 processor, whereas ResNet50 can only manage about 12 frames per second.

3.4. Comparative Analysis of Feature Extraction Networks

Through systematic analysis of the aforementioned feature extraction networks, this study compares mainstream models such as 3D CNN, ConvLSTM, and GhostNet within a unified

evaluation framework. Table 3-1 presents a comprehensive performance comparison on the RWF-2000 dataset. In terms of computational resource requirements, GhostNet demonstrates significant advantages for deployment on edge devices with its 5.2 million parameters and computational load of 0. 41 GFLOPs. Although the 3D CNN achieves high performance with an accuracy rate of 92.3%, its parameter count (26.7 million) and computational overhead (4.3 GFLOPs) are significantly higher than those of the other networks, limiting its application in resource-constrained scenarios [5, 6].

Table 1. Comprehensive Performance Comparison Table of 3D CNN, ConvLSTM, and GhostNet on the RWF-2000 Dataset

Network Type	Parameter Quantity (M)	Ccomputational Load (GFLOPs)	Accuracy (%)	Time to Reason (ms/frame)	Applicable Scenarios
3D CNN	26.7	4.3	92.3	42	High-precision requirement scenarios
ConvLSTM	15.3	2.8	89.6	28	Long-Term Sequential Behavior Analysis
GhostNet	5.2	0.41	87.2	12	Edge computing devices

From a practical application perspective, the selection of feature extraction networks should balance accuracy and efficiency requirements: High-security scenarios are suitable for 3D CNNs; In resource-constrained environments, GhostNet is a viable option; For scenarios requiring the capture of long-term behavioral evolution, ConvLSTM demonstrates superior performance.

4. Research on Multimodal Information Fusion Strategies

4.1. Early Integration Strategy

4.1.1. Principles and Methods of Early Integration

Early fusion serves as a foundational approach in multimodal learning, operating at the data or low-level feature stage. In this paradigm, raw data or shallow features from multiple modalities are integrated — either prior to or during initial feature extraction — and subsequently processed via a unified network. A major strength of this strategy is its ability to facilitate cross-modal interaction learning from the earliest stage, thereby promoting richer joint representations. Nonetheless, it is highly sensitive to inter-modal alignment and quality, as inconsistencies or noise in any modality can adversely affect the entire system. Typical techniques include direct concatenation of feature vectors along the channel axis, weighted fusion with fixed or adaptive weights, and tensor fusion based on outer products to model cross-modal correlations [7].

4.1.2. Representative Task Analysis

In the field of violent behavior recognition, several representative studies employing early fusion strategies have emerged in recent years. The ConvLSTM network architecture is employed to fuse visual and audio features during the initial stage of feature extraction. Specifically, the audio signal is first converted into a Mel-spectrogram. They are then concatenated with the video frames in the feature dimension and feed into the ConvLSTM network. This method demonstrates excellent computational efficiency, enabling real-time processing, but its accuracy decreases in complex scenarios [6].

4.1.3. Performance on the RWF2000 dataset

The early fusion method based on 3D CNN achieved an average accuracy of 78.6% on the RWF-2000 dataset, with Xu et al. 's work attaining an accuracy of 77.3%. Subsequent improved versions increased this figure to 80. 1%. The early fusion method using ConvLSTM achieves an average accuracy of 76.2%, slightly lower than the 3D CNN approach, but offers faster inference speeds, making it more advantageous in resource-constrained environments.

4.2. Late-stage Integration Strategy

4.2.1. Principles and Methods of Late Fusion

Late-stage fusion is a crucial integration strategy in multimodal violent behavior recognition; its core idea is to first process data from each modality through an independent feature extraction network to obtain high-level, modality-specific representations, which are then fused at later stages—either at the feature layer or the decision layer.

Late fusion is typically achieved through the following methods: the feature cascade method, which directly concatenates feature vectors extracted from different modalities before feeding them into the classifier; the score fusion method, each modality performs classification independently and obtains confidence scores, which are then fused using rules such as weighted averaging, maximum value, or multiplication; and the model cascading method, Constructing fusion layers at different levels to progressively integrate features from various modalities. The primary advantage of this strategy lies in the relative independence of each modality processing path, facilitating the design of specialized networks tailored to distinct modality characteristics. Furthermore, the system exhibits enhanced robustness when a particular modality is missing or noisy.

4.2.2. Representative Task Analysis

In recent years, late fusion has achieved significant results in the identification of violent behavior. Researchers proposed a late fusion method based on a dual-stream network. They used ResNet-50 was to extract RGB image features, while FlowNet was employed to extract optical flow features. These features were then fused through feature concatenation, achieving an accuracy of 94.2% on the Hockey Fight dataset.

There is also a layered advanced fusion framework. First, use ConvLSTM and GhostNet to extract temporal features and appearance features, respectively. Then, through the attention mechanism, intra-modal feature optimization is performed. Finally, cross-modal fusion is achieved through a fully connected layer. This method achieves a good balance between computational efficiency and recognition accuracy, with only 6.7 million parameters — approximately 30% fewer than comparable approaches — while maintaining an accuracy rate of 89. 3% on the RWF-2000 dataset.

4.2.3. Performance on datasets such as RWF2000

Experiments on the RWF-2000 dataset demonstrate that late fusion strategies generally outperform single-modality approaches. According to 2022 statistics, the average accuracy of late-stage fusion multimodal methods reached 89. 7%, approximately 3. 5 percentage points higher than that of single-visual-modality methods. The advantages of late fusion become particularly evident in low-light conditions and complex background scenarios, where accuracy improvements can reach 5% to 8% [8].

4.3. Attention Fusion Strategy

4.3.1. Principles and Methods of Attention Fusion

Attention-based fusion strategies represent a sophisticated approach to multimodal information fusion. The core idea is to dynamically learn importance weights for different modalities, enabling context-aware and adaptive integration of features. This is primarily realized through three fundamental mechanisms: channel attention, which emphasizes informative feature channels; spatial attention, which focuses on critical regions within feature maps; and temporal attention, which identifies key segments in video sequences.

In violent behavior recognition, attention-based fusion is commonly implemented using Transformer architectures, self-attention mechanisms, and cross-attention mechanisms, each serving distinct roles:

Self-Attention is used to model intra-modal dependencies. For example, it can capture relationships between different body parts in skeleton data or between objects in an RGB video frame, enhancing feature representation within a single modality.

Cross-Attention enables interaction between modalities by using one modality (e.g. audio) to guide the attention distribution in another (e.g. video). This is especially useful for emphasizing discriminative features complementary across modalities, such as correlating aggressive sounds with specific motion patterns.

Spatiotemporal Attention combines both spatial and temporal reasoning, allowing the model to jointly focus on critical regions (e.g. limbs in motion) and key moments (e.g. sudden movements) in video sequences, thereby improving recognition accuracy for dynamic violent behaviors.

A typical implementation involves first computing attention weights for each modality or across modalities, and then performing weighted fusion of the features. This adaptive weighting mechanism not only improves representation effectiveness but also enhances robustness to noise and missing modalities.

4.3.2. Representative Task Analysis

In the field of attention fusion strategies, several representative studies have achieved significant results. Researchers proposed a fusion framework based on spatio-temporal attention, which incorporates a bidirectional LSTM network to model temporal features and employs a self-attention mechanism to capture interactions between visual and audio modalities. Experiments demonstrate that this method achieves a 4. 8% improvement in recognition accuracy over traditional approaches in violent scene identification. Researchers developed a cross-modal attention fusion mechanism that guides audio attention allocation through visual features and vice versa, achieving complementary enhancement across modalities. This method achieved a recognition accuracy of 92. 1% in scenarios involving rapid violent actions [9].

4.3.3. Performance on the RWF2000 dataset

On the RWF-2000 dataset, the attention fusion strategy demonstrates significant advantages. The latest data indicates that in 2023, multi-modal attention fusion methods based on the Transformer architecture achieved an accuracy rate of 96. 8%. It increased by 5. 2 percentage points compared to the 2020 baseline level. Specifically, the approach combining GhostNet with a bidirectional cross-attention mechanism reduces model parameters by 37% while maintaining high accuracy, and boosts inference speed by 41%. This proves particularly effective in surveillance scenarios demanding high real-time performance.

In terms of computational efficiency, lightweight attention fusion models also demonstrate feasibility on edge devices. The approach combining MobileNetV3 with channel attention achieves a processing speed of 16 FPS on the Raspberry Pi 4 while maintaining a recognition accuracy of 90. 3% [9, 10].

4.4. Analysis of Coupling Effects Between Feature Extraction Networks and Fusion Strategies

4.4.1. The Impact of Different Network Structures on Fusion Performance

Feature extraction networks, as the preliminary stage of multimodal fusion, have structural characteristics that directly impact fusion performance. Through research and analysis, it was found that different network structures exhibit significant differences in their fusion performance.

Compute-intensive networks (e.g. 3D CNNs) are ideal for early fusion strategies due to their strong capacity in learning complex spatio-temporal features directly from fused raw data across modalities.

Sequence-aware architectures (e.g. ConvLSTM) are naturally suited for late fusion strategies. Their ability to capture long-range temporal dependencies within unimodal sequences allows effective modeling of modality-specific dynamics before integrating high-level decisions. This is evidenced by a 3.2% accuracy gain over conventional LSTMs on the Hockey Fight dataset.

Lightweight networks (e.g., GhostNet) pair effectively with attention fusion mechanisms. Although such networks have reduced representation capacity—exemplified by GhostNet having only one-quarter the parameters of a 3D CNN—attention modules compensate by dynamically highlighting critical features. This combination enables high efficiency with minimal performance loss (only 2.1% accuracy degradation), making it especially suitable for edge deployment.

4.4.2. Analysis of Integration Strategy Benefits for Network Performance

Fusion strategies, serving as bridges connecting information from different modalities, yield significant performance gains for neural networks. Early fusion strategies provide rich input information for structures such as 3D CNNs by merging raw data prior to feature extraction. In scenarios with sufficient computational resources, it enables the network to learn cross-modal features end-to-end. Compared to single-modal methods, it achieves an average improvement of 6. 8% in recognition accuracy. However, early fusion yields limited gains for sequence models like ConvLSTM, improving performance by only 1. 2%, indicating that the compatibility between fusion strategies and network types is crucial.

The late fusion strategy performs best on ConvLSTM networks. By extracting features from each modality separately and then fusing them, modality-specific information is preserved, enhancing the model's ability to distinguish contributions from different modalities. According to 2021 research data, late fusion can improve the violent detection accuracy of ConvLSTM in CCTV surveillance scenarios by 7.5%, while only achieving a 3.1% improvement on 3D CNNs. The attention fusion strategy significantly enhances GhostNet's performance through adaptive weight allocation, particularly in noisy environments. The attention mechanism enables GhostNet to maintain low computational complexity while improving detection accuracy by 8.3%.

4.4.3. Optimal Portfolio Selection Under Resource Constraints

In practical deployment scenarios, resource constraints are the key factor in selecting the optimal “network-convergence” combination. Based on a systematic analysis of current research findings, three optimal combinations can be identified for typical application scenarios. In high-performance server environments, 3D CNNs paired with early fusion strategies deliver optimal performance, making them suitable for resource-rich scenarios such as security monitoring centers. On edge computing devices, GhostNet combined with attention fusion strategies is an ideal choice, suitable for constrained devices such as smart cameras. In scenarios demanding high real-time performance, such as smart city surveillance systems, lightweight ConvLSTM paired with late fusion strategies proves most efficient.

5. Conclusion

This paper provides a systematic review and analysis of violent behavior recognition methods based on multimodal information fusion, focusing on a dual-mainline framework centered around “feature extraction networks and multimodal fusion strategies.” By systematically reviewing representative studies, this research compares the combined effects of different feature extraction networks and fusion strategies within a unified experimental framework, thereby filling a gap in existing research.

Research has found that in feature extraction networks, lightweight networks such as GhostNet, despite reducing the number of parameters by 78%, only saw a 3. 2% decrease in recognition accuracy on the RWF-2000 dataset, demonstrating their advantages for deployment on edge devices. Regarding fusion strategies, the attention-based fusion approach achieved an average accuracy improvement of 4. 7% compared to early and late fusion methods, demonstrating particularly outstanding performance in heterogeneous modality combinations.

Through systematic induction and quantitative comparison, it provides clear guidance for researchers to select appropriate feature extraction networks and fusion strategies in practical applications. This research holds significant reference value for advancing the practical deployment of violent behavior recognition technology in security surveillance, public venue safety, and related fields.

This study highlights several technical limitations in current violent behavior recognition research based on multimodal fusion. First, while covering major works since 2019, the rapid evolution of methods means some innovative approaches may not be included. Second, inconsistencies in

implementation details across models — such as hyperparameter settings and training strategies — may affect the fairness of comparative evaluations.

At the data level, available benchmarks such as RWF-2000 remain limited in scene diversity and cultural contexts, restricting generalizability to real-world environments. Furthermore, the interaction between fusion strategies and feature extraction networks has not been thoroughly investigated, and a cohesive theoretical framework explaining their combined effects is still lacking. These aspects represent important directions for future work.

Future research in multimodal violent behavior recognition may focus on several key directions: developing lightweight networks for efficient edge deployment, advancing cross-modal self-supervised learning to improve generalization with limited labels, and designing dynamic fusion mechanisms that adapt to noisy or missing modalities. Privacy-preserving algorithms for sensitive scenarios and multi-scenario transfer learning methods to enhance cross-domain adaptability also represent critical areas for further exploration. Advances in these domains will promote broader and more reliable applications in public security.

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