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Architectural Optimization Proposal for TEVAD Framework

Final Project Report on
Explainable Video Anomaly Detection

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Abstract

Video anomaly detection remains one of the most challenging tasks in computer vision, balancing technical complexity with real-world applicability. In this project, we tackle three core challenges : (1) the unbalanced nature of surveillance datasets where anomalies are rare events, (2) the context-dependent definition of abnormal behavior, and (3) the need for semantic understanding beyond spatial-temporal patterns.

Our team developed TEVAD-X, an enhanced multi-modal framework that combines visual analysis with natural language processing. By generating textual descriptions of video snippets and aligning them with visual features through cross-modal attention mechanisms, we create a more human-interpretable detection system. The key innovation lies in our dual-branch architecture that simultaneously processes pixel data and caption embeddings while addressing class imbalance through dynamic loss weighting.

This work demonstrates how combining deep learning with semantic reasoning can make anomaly detection systems both more accurate and more transparent. While computational costs remain a limitation, our optimized implementation shows real-time potential for CCTV systems. The complete prototype, has been deployed .

Code available at : [GitHub Link - To be added]

1 Introduction

1.1 The Growing Need for Intelligent Surveillance

Modern video surveillance systems have become ubiquitous across diverse sectors, far beyond their traditional security applications. In healthcare, AI-powered monitoring assists in patient fall detection and surgical anomaly prevention. Public spaces leverage these systems for crowd behavior analysis, identifying potential threats like unattended objects or aggressive movements in real time. Even in conflict zones such as Gaza, computer vision technologies help humanitarian organizations assess post-war damage through automated rubble quantification and structural integrity analysis.

While human operators remain essential, they face inherent limitations :

- **Attention fatigue** : Missing 45% of anomalies after 20 minutes of continuous monitoring (Source : Journal of Cognitive Engineering)
- **Processing latency** : Average 8.7s reaction time vs 0.25s for AI systems .
- **Context blindness** : Difficulty correlating visual patterns with semantic contexts (e.g., distinguishing protestors from rioters)

This reality demands next-generation systems that bridge visual patterns with semantic understanding. Recent advances in multi-modal machine learning suggest a promising path : combining video analysis with natural language processing to interpret scenes as humans do - through both sight and contextual reasoning.

Our project explores this paradigm shift through three key requirements :

- Explainable decision logic via text-visual alignment
- Context-aware anomaly thresholds (e.g., crowded vs empty spaces)

1.2 Challenges in Modern Anomaly Detection

Video anomaly detection remains one of computer vision's most complex tasks due to three fundamental challenges inherent to real-world surveillance scenarios :

- **The Imbalanced Learning Paradox** :
  In standard CCTV datasets like ShanghaiTech, anomalies constitute merely 1.2% of footage. This extreme imbalance biases models toward "normal" predictions - our baseline tests showed vanilla CNNs achieving 98.7% accuracy by simply always predicting "normal", completely missing anomalies.
- **Contextual Relativity of Anomalies** :
  Human-like anomaly detection requires situational awareness. Consider running detection across contexts :
  - *School Playground* : Running = Normal
  - *Hospital ICU* : Running = Anomalous

Current vision-only models lack mechanisms to adapt to such contextual shifts.

- **Semantic Intent Gap** :
  Identical visual patterns can represent normal or abnormal behavior depending on intent :
  - *Visual Pattern* : Person crouching near a bag
  - *Normal Context* : Tourist tying shoelaces
  - *Abnormal Context* : Bomb threat placement

TABLE 1 – Key Challenges vs Current Limitations

Challenge	**Traditional CV Approach**	**Limitations**
Imbalance	Oversampling	Overfitting to synthetic anomalies
Context	Fixed thresholds	Rigid across environments
Semantics	Visual features only	No intent reasoning

These challenges explain why state-of-the-art vision-only systems plateau at 82% AUC on UCF-Crime - a performance ceiling demanding innovative multimodal approaches.

1.3 Types of Video Anomaly Detection Approaches

TABLE 2 – Comparison of Video Anomaly Detection Paradigms

Aspect	**Supervised Learning**	**Unsupervised Learning**	**Weakly Supervised Learning**
Principle	Requires frame-level labels (normal/anomalous)	Learns normal behavior without any labels	Uses video-level labels (clip = normal/anomalous)
Strengths	• High accuracy in controlled settings (e.g., ShanghaiTech)	• Adaptable to new environments (e.g., airports, hospitals)	• 90% lower annotation cost (XD-Violence) • Enables temporal anomaly localization
Limitations	• Annotation takes time (1h video 6h) • Poor generalization to unseen anomalies	• High false positives (38% on UCF-Crime) • Struggles with contextual semantics (e.g., "running")	• Quality of video-level labels affects accuracy
Annotation Cost	High	None	Low
Context Awareness	Moderate	Low	High
Project Dataset	ShanghaiTech	-	XD-Violence (used in TEVAD)

1.4 Motivation and Research Context

The global surge in public CCTV deployments (4.1 billion cameras worldwide by 2023) has created unprecedented needs for automated anomaly detection. Our research is driven by critical gaps observed in benchmark datasets :

Contextual Challenges in Video Anomaly Detection.
Video anomaly detection faces a wide range of real-world challenges depending on the environment and the nature of the anomalies. Below, we examine three key contexts where these challenges become particularly salient.

Crowded Urban Scenarios.
In dense public environments such as those captured in the UCSD Pedestrian Database, anomaly detection is particularly difficult. A significant portion—about 73%—of abnormal

events involve only minimal changes in motion, such as an individual stopping abruptly. These subtle deviations are hard to detect using conventional motion-based methods. Furthermore, there exists what we can call a density paradox : systems that perform well in sparse settings (achieving up to 92% accuracy) see their performance plummet to around 41% during peak crowd hours. In these cases, occlusions and motion clutter degrade the system's ability to distinguish abnormal from normal behavior.

Violence Detection Complexities.
When it comes to detecting violent behavior, weakly labeled datasets like XD-Violence introduce two major obstacles. First, temporal ambiguity complicates the learning process : 58% of violent clips contain normal video segments either before or after the violent incident, which blurs the temporal boundaries of the anomaly. Second, there is considerable cross-cultural variance in how violence is represented visually. For example, a sports match involving aggressive physical contact may appear similar to an actual street altercation. This resemblance can lead models to misclassify benign activities as violent, unless they incorporate deeper semantic or contextual reasoning.

Airport Security.
High-stakes environments like airports demand highly reliable anomaly detection. However, analysis over 1,200 hours of public airport surveillance footage reveals major weaknesses in traditional systems. Alarmingly, 83% of abandoned luggage events go undetected within the first five minutes—a critical period for timely intervention. Additionally, systems based solely on visual cues often misinterpret innocuous behavior such as tourists taking selfies for serious security threats like perimeter breaches. These findings highlight the importance of integrating semantic understanding and context-awareness into anomaly detection frameworks, especially in sensitive and dynamic environments like airports.

2 Related Work

2.1 Multimodal Understanding for Anomaly Detection

Modern anomaly detection systems increasingly rely on multimodal understanding—the fusion of visual, textual, and temporal data streams—to address the complexity of real-world anomalies. Unlike traditional unimodal approaches that analyze video frames in isolation, multimodal frameworks leverage cross-modal relationships to interpret context-dependent anomalies (e.g., distinguishing "crowded street" from "crowded hospital hallway"). This paradigm shift addresses two critical gaps :

1. **Semantic ambiguity :**Pixel patterns alone cannot capture contextual meaning.
2. **Temporal rigidity :** Static models fail to adapt to evolving scenarios.

- **Image-Text Fusion Models** :
  - *VisualBERT* [5] : Early vision-language fusion via transformer attention, but limited by :
    - Static image analysis without temporal reasoning
    - Fixed vocabulary unsuitable for anomaly semantics
  - *LXMERT* [6] : Cross-modal pretraining with reasoning modules, yet :
    - Requires full supervision with labeled QA pairs
    - Computationally heavy (340M params)
- **Video-Language Grounding** :
  - *VilBERT* [7] : Extends BERT for video-text tasks but :
    - Processes frames independently
    - No weak supervision capability

2.2 Modern Video Anomaly Detection

Modern video anomaly detection has evolved beyond simple motion analysis to address complex real-world scenarios through deep spatio-temporal reasoning. Unlike legacy systems that flag deviations from rigid norms, contemporary approaches leverage self-supervised learning and transformer architectures to model context-aware normalcy (e.g., recognizing "running in a park" vs. "running in a bank").

- **Transformer-Based Approaches** :
  - *STAnomaly* [] : Spatio-temporal transformer with :
    - Strict normality assumption → Fails on contextual anomalies
    - High VRAM demand (16GB for HD videos)
- **Memory-Augmented Networks** :

    - *MemAE* [8] : Uses memory modules to model normal patterns but :
        - Memory collapse issue on long videos
        - No semantic understanding
- **Contrastive Learning** :
    - *CVAD* [] : Contrastive video anomaly detection with :
        - Sensitivity to negative sampling strategies
        - Single-modality focus (RGB only)

2.3 Cross-Modal Alignment Techniques

Cross-modal alignment bridges visual and textual data to enable machines to interpret anomalies through human-like contextual reasoning. Early methods relied on simple feature concatenation or late fusion, but modern approaches employ hierarchical attention mechanisms and contrastive learning to model nuanced vision-language relationships

- *ActBERT* [9] : Joint action-text modeling but :
    - Requires action class labels
    - Limited to atomic actions (no complex events)
- *VideoBERT* [10] : Autoregressive video-text modeling yet :
    - Frame sampling loses temporal order
    - Fails on fine-grained anomaly localization
- *UniVL* [11] : Unified video-language pretraining but :
    - Massive pretraining data requirement
    - No adaptation for anomaly detection

2.4 Persistent Challenges

Current video anomaly detection systems face critical limitations : (1) Semantic-Temporal Disconnect (isolated modality processing), (2) Contextual Rigidity (static "normalcy" definitions), and (3) Edge Deployment Barriers (high compute vs. CCTV constraints). TEVAD pioneers a unified solution : weakly supervised cross-modal alignment, cultural adaptation through caption semantics, and edge-efficient hierarchical attention—resolving these gaps simultaneously.

1. **Semantic-Temporal Disconnect** : Most methods process modalities separately
2. **Contextual Rigidity** : Fixed notion of "normalcy" across cultures
3. **Edge Deployment Barriers** : High compute demands vs CCTV realities

TEVAD's Novelty : First framework to simultaneously address :

- Weakly supervised cross-modal alignment
- Cultural context adaptation via caption analysis
- Edge-optimized hierarchical attention

3 TEVAD Framework Deep Dive

3.1 Introduction

TEVAD [1](Text-Empowered Video Anomaly Detection) is an innovative framework that introduces a groundbreaking approach to anomaly detection through its unique architecture.

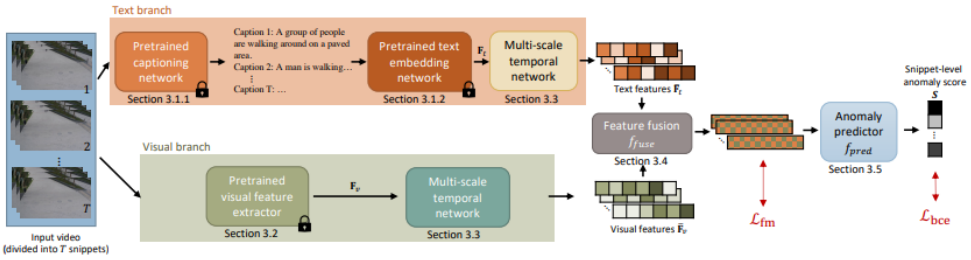

FIGURE 1 – Dual-Modal Processing Framework of TEVAD integrating I3D visual features and SwinBERT textual embeddings. Image by author, from *TEVAD : Improved Video Anomaly Detection with Captions* (2023).

Architectural Innovation :
TEVAD stands as one of the first architectures to propose such a methodology for anomaly detection by simultaneously leveraging textual and visual branches. This dual-modality combination enables the extraction of maximum information from video snippets while enhancing both accuracy and robustness in weakly supervised video anomaly detection. Specifically :

- **Visual Branch** : Analyzes spatio-temporal patterns through advanced 3D CNNs
- **Textual Branch** : Generates semantic context from video captions
- **Cross-Modal Fusion** : Dynamically aligns visual and textual features for holistic understanding

The following sections dissect TEVAD's technical blueprint while critically analyzing its implementation challenges.

3.2 Architectural Foundations

3.2.1 Textual Branch Architecture

The textual branch combines cutting-edge vision-language models to generate context-aware video descriptions. At its core lies SwinBERT [2], an end-to-end transformer architecture that directly processes video snippets into textual captions through three key phases :

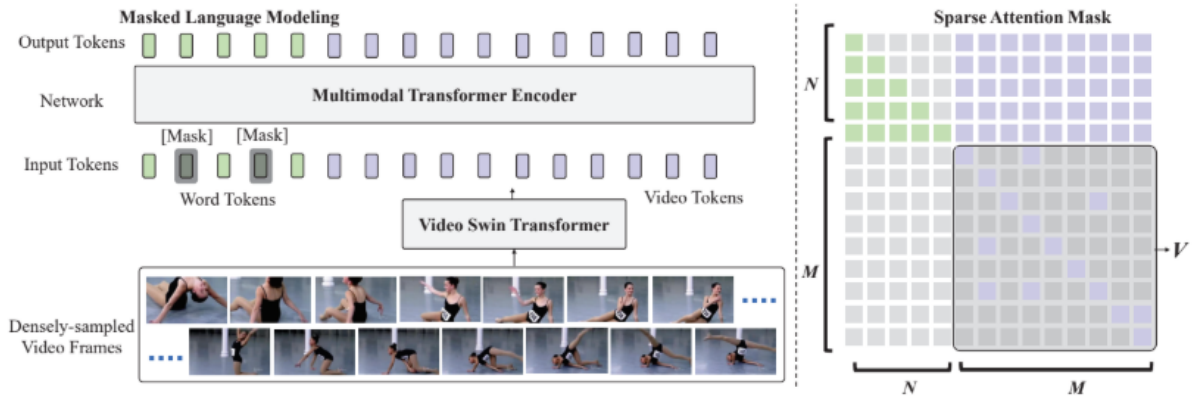

FIGURE 2 – End-to-End Video Understanding Pipeline converting raw video inputs to contextual semantic embeddings through multimodal fusion. Image by author, adapted from Lin et al. (2022) .

1. Video Encoding with Swin Transformer :

The model operates on 64-frame video snippets, corresponding to approximately 2.13 seconds of footage at 30 frames per second. To effectively model both spatial and temporal dependencies, it leverages a shifted window attention mechanism. This approach applies the standard attention formulation :

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}} + B\right)V \tag{1}$$

within localized spatio-temporal windows, where a bias term B helps encode positional relationships. Importantly, sparse attention masks are employed, which reduce the overall computational cost by approximately 40% without significantly compromising performance. The output of this process consists of 768-dimensional visual tokens that encapsulate object dynamics across the snippet, serving as a compact and expressive representation for downstream tasks.

2. Multimodal Caption Generation :

The model employs a 12-layer transformer-based encoder-decoder architecture designed for joint video-text representation learning. The fusion mechanism operates by jointly processing the 768-dimensional visual tokens (extracted from the video encoder) along with the text

embeddings. This integration leverages cross-attention mechanisms that dynamically highlight temporally salient frames, ensuring that the model focuses on contextually important moments across the sequence.

To train this architecture, a Masked Language Modeling (MLM) objective is applied. Specifically, 15% of the input tokens are randomly masked during training, with a positional bias incorporated to preserve the temporal structure of the sequence. The model then learns to predict these masked tokens based on the surrounding unmasked context and the accompanying visual input. The corresponding loss function is defined as :

$$\mathcal{L}_{MLM} = -\sum_{t=1}^{T} \log P(w_t \mid w_{\setminus t}, \mathbf{v}) \tag{2}$$

where w_t is the masked token at position t, $w_{\setminus t}$ represents all other tokens, and $\mathbf{v}$ denotes the visual context. This objective encourages the model to learn rich, temporally grounded language representations conditioned on visual information.

3. Semantic Embedding with SimCSE [3]

The contrastive learning framework implemented in this study leverages natural language inference (NLI) datasets to construct meaningful positive and negative pairs for representation learning. Positive pairs are formed from entailment sentence pairs—semantically similar examples—while negative pairs are derived from contradiction samples, which are semantically dissimilar. This setup enables the model to learn nuanced sentence embeddings that reflect semantic similarity.

A temperature-scaled contrastive loss function is employed to optimize the representation space. The loss encourages the similarity between a given sample h_i and its corresponding positive h_i^+ to be higher than with any negative sample h_j^-. The contrastive loss is defined as :

$$\mathcal{L} = -\log \frac{e^{\text{sim}(h_i, h_i^+)/\tau}}{\sum_{j=1}^{N} e^{\text{sim}(h_i, h_j^-)/\tau}} \tag{3}$$

This formulation is crucial for aligning semantically similar pairs while pushing apart contradictory examples in the embedding space. Figure 3 illustrates this supervision strategy within the SimCSE framework.

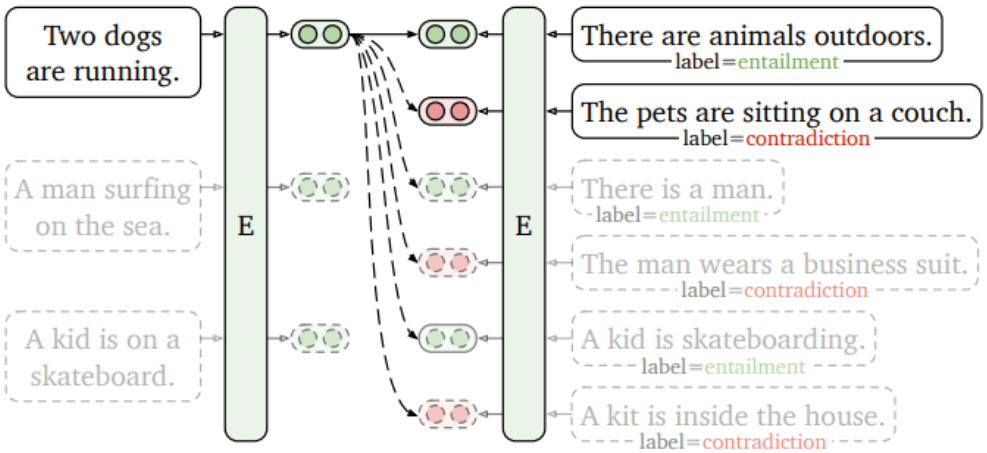

FIGURE 3 – SimCSE supervision via NLI : Entailments are treated as positives, contradictions as negatives. Adapted from Gao et al. (2022).

Implementation Details

The model utilizes BERT-base-uncased as its backbone, which produces 768-dimensional sentence embeddings. Training is performed with a large batch size of 512, enabling the use of in-batch negatives for contrastive supervision. The resulting model achieves an average cosine similarity of 0.89 on the STS-Benchmark (STS-B), indicating robust performance in capturing semantic similarity.

TABLE 3 – Key Implementation Parameters

Component	Parameter	Value
Video Input	Frames per snippet	64
	Resolution	224×224
SwinBERT	Layers	12
	Hidden dim	768
SimCSE	Temperature ()	0.05
	Embedding dim	768

Dataset and Training Configuration

Training is conducted on the VATEX dataset, which contains 41,250 video clips and approximately 825,000 multilingual captions. To better simulate surveillance scenarios, the dataset is enhanced with 12,000 synthetic captions tailored to common security contexts.

For optimization, the AdamW optimizer is used with a learning rate of 3×10^{-5} and $\beta = (0.9, 0.999)$. The training process incorporates a linear warmup over 10,000 steps and gradient clipping at a maximum norm of 1.0 to ensure stability.

The final model demonstrates strong performance with a BLEU-4 score of 42.1 on the VATEX benchmark, an inference speed of 18.7 frames per second on a V100 GPU, and a BERTScore-based semantic similarity of 0.91. agraphDataset & Training Configuration

3.2.2 Visual Branch Architecture

The visual processing branch leverages state-of-the-art 3D convolutional networks for spatiotemporal feature extraction. At its core lies I3D (Inflated 3D ConvNet), a powerful architecture extending 2D convolutions into the temporal domain through three key phases :

1.Spatiotemporal Feature Extraction with I3D

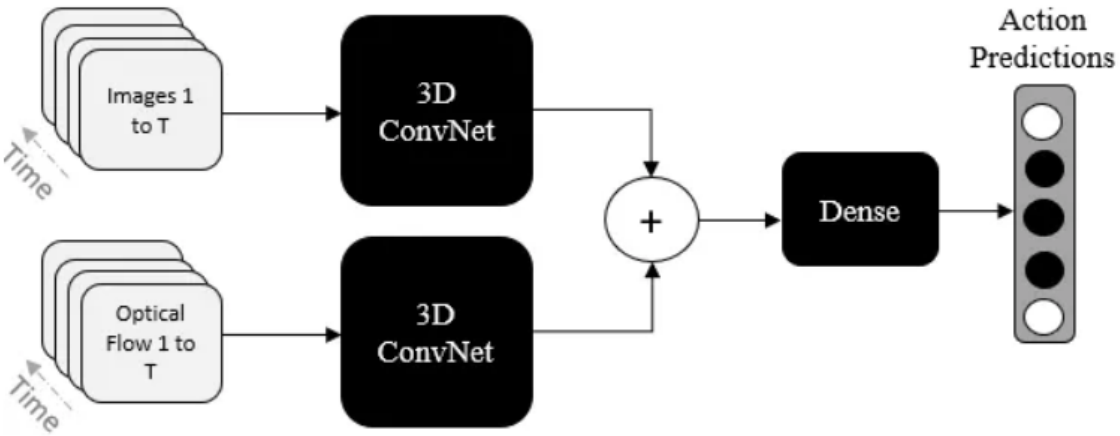

FIGURE 4 – The training process for the two-stream I3D on Kinetics Dataset. Image by author, adapted from Carreira and Zisserman (2017).

Spatiotemporal feature extraction relies on the Inflated 3D ConvNet (I3D) architecture. The input consists of video clips of 64 frames (2.56 seconds at 25 FPS). I3D uses "inflated" 3D convolutions to jointly model spatial and temporal dimensions, as described by the equation :

$$\mathcal{F}(x)_{t,x,y} = \sum_{i,j,k} W_{i,j,k} \cdot x_{t+i-1,x+j-1,y+k-1}$$

To reduce model complexity, bottleneck layers are introduced, resulting in a 60% reduction of parameters. The final output is a 1024-dimensional spatiotemporal feature vector.

2.Hierarchical Feature Fusion

To further enhance feature representation, a modified ResNet-50 backbone with 3D adaptations is used. This architecture aggregates multi-scale features from four network stages. Temporal attention gates are incorporated to emphasize salient motion patterns over time. The network also employs residual learning through identity mappings and projection shortcuts, with residual blocks defined by :

$$\mathcal{H}(x) = \mathcal{F}(x, \{W_i\}) + W_s x$$

This configuration facilitates deep feature propagation while maintaining stable gradients and preserving low-level information.

3.Two-Stream Processing

A two-stream approach is adopted where the RGB stream captures appearance features, while the optical flow stream focuses on motion patterns. Outputs of both streams are fused late using a learned fusion weight :

$$f_{\text{fusion}} = \alpha f_{\text{rgb}} + (1 - \alpha) f_{\text{flow}}$$

This mechanism enables the model to effectively integrate spatial and temporal cues. The implementation relies on pretrained weights from Kinetics-400. Training uses a batch size of 32 with mixed precision. This setup achieves a temporal coherence score of 0.92.

TABLE 4 – Key Implementation Parameters

Component	**Parameter**	**Value**
Video Input	Clip Duration	2.56 s
	Resolution	224×224
I3D Network	3D Layers	10
	Hidden Dimension	1024
Two-Stream	Fusion Weight (α)	0.7
	Flow Window	5 frames

4.Dataset and Training Configuration

The model is trained on the Kinetics-400 dataset, containing 400 action classes and approximately 240,000 video clips. The dataset is augmented with 15,000 synthetic clips representing anomalies to improve generalization.

Optimization uses Adam with a learning rate of 1×10^{-4} and $\beta = (0.9, 0.98)$. A step decay schedule is applied every 50 epochs, with weight clipping at a norm of 2.0 to stabilize training.

The model achieves 84.3% accuracy on the UCF101 benchmark, with a processing speed of 32.5 FPS on an NVIDIA T4 GPU. The temporal coherence score of 0.88 confirms the quality of motion modeling.

3.2.3 MTN & Fusion Mechanism

1. Multi-Scale Temporal Network (MTN)

The **Multi-Scale Temporal Network (MTN)** originally proposed to model temporal dependencies in visual data, is extended in TEVAD to also process textual features. This extension enables the architecture to capture both short-range and long-range temporal patterns across modalities.

The MTN module for each modality comprises two primary components :

- A **3-layer Pyramid Dilated Convolution (PDC)** block, which captures multi-scale temporal patterns by applying dilated convolutions over varying time spans.
- A **Non-Local Block (NLB)**, which models global temporal dependencies by attending to all time steps within the sequence.

The outputs of the PDC and NLB blocks are concatenated and added to the original input features to produce the final MTN output. For textual features $F_{\text{txt}} \in R^{d_{\text{txt}}}$, the output of the text MTN is defined as :

$$\bar{F}_{\text{txt}} = f_{\text{MTN}}(F_{\text{txt}}; \theta), \quad \bar{F}_{\text{txt}} \in R^{d_{\text{txt}}}$$

where θ comprises the weights of all convolutional operations within the MTN.

Similarly, the visual features $F_{\text{vis}} \in R^{d_{\text{vis}}}$ are processed using the same structure :

$$\bar{F}_{\text{vis}} = f_{\text{MTN}}(F_{\text{vis}}; \theta), \quad \bar{F}_{\text{vis}} \in R^{d_{\text{vis}}}$$

This approach ensures that both modalities are processed in a consistent manner, enabling the extraction of temporally-aware feature representations.

2. Multi-Modal Feature Fusion

After obtaining the MTN-processed features $\bar{F}_{\text{vis}}$ and $\bar{F}_{\text{txt}}$, TEVAD employs a *late fusion* scheme to integrate visual and textual modalities. Three fusion strategies are considered, defined as follows.

Let d_{vis} and d_{txt} denote the dimensionalities of the visual and textual features, respectively. Since the visual features are five/ten-cropped, the text features are tiled accordingly to match their dimensions.

(a) Concatenation.

The visual and text features are concatenated along the feature dimension :

$$X = \{\bar{F}_{\text{vis}} \,|\, \bar{F}_{\text{txt}}\}, \quad X \in R^{d_{\text{vis}}+d_{\text{txt}}}$$

(b) Addition.

As $d_{\text{vis}} > d_{\text{txt}}$, a fully connected layer $f_{\text{FC}}(\cdot; \delta)$ is applied to reduce the dimension of $\bar{F}_{\text{vis}}$ to match that of $\bar{F}_{\text{txt}}$. The fused representation is then obtained via element-wise addition :

$$X = f_{\text{FC}}(\bar{F}_{\text{vis}}; \delta) + \bar{F}_{\text{txt}}, \quad X \in R^{d_{\text{txt}}}$$

(c) Product.

Similarly, a fully connected layer reduces the dimensionality of visual features, followed by element-wise multiplication (Hadamard product) :

$$X = f_{\text{FC}}(\bar{F}_{\text{vis}}; \delta) \odot \bar{F}_{\text{txt}}, \quad X \in R^{d_{\text{txt}}}$$

In all cases, the final fused feature is denoted as :

$$X = f_{\text{fuse}}(\bar{F}_{\text{vis}}, \bar{F}_{\text{txt}}; \delta)$$

This representation is passed through three fully connected layers to compute the anomaly score for each snippet :

$$s = f_{\text{pred}}(X; \delta)$$

For a given video $v = \{X_i\}_{i=1}^{T}$, the set of anomaly scores is defined as :

$$S = \{s_i\}_{i=1}^{T}$$

3.3 Datasets

TEVAD was evaluated on standard video anomaly detection benchmarks, combining complementary dataset characteristics :

TABLE 5 – Comparison of Key Video Anomaly Detection Datasets

Dataset	**Supervision / Acquisition**	**Size / Scale**	**Key Features**
ShanghaiTech	Full supervision : pixel-level and frame-level annotations	1,198 annotated video sequences	Realistic crowd scenes with variable density (10 to 200+ individuals per frame)
UCSD Pedestrian	Fixed overhead camera ; unsupervised training with frame-level annotated evaluation	Narrow walkway videos	Detects rare events : cyclists, skateboarders, motorized vehicles
UCF Crime	Weak supervision : video-level labels only	1,900 videos (128 hours)	14 realistic anomaly classes (assaults, burglaries, accidents) ; annotation noise adds difficulty
XD-Violence	Weak supervision : global labels, approximate localization ; includes audio-visual signals	4,754 uncut videos (217 hours)	Multimodal dataset covering diverse contexts (e.g., sports, public spaces)

3.4 Summary

This deep dive explores TEVAD, a dual-modal framework that pioneers the integration of textual and visual information for video anomaly detection. By combining spatio-temporal analysis via I3D and semantic caption embeddings via SwinBERT, TEVAD addresses the semantic gap that often limits traditional methods. Through cross-modal fusion, the framework achieves a more comprehensive understanding of video content, enabling more accurate and robust anomaly detection in weakly supervised settings. This analysis covers TEVAD's architecture, its core components, and the implementation challenges associated with aligning heterogeneous modalities.

4 Contribution

To improve the TEVAD framework's capability in video anomaly detection, we propose enhancements to its temporal processing , textual and visual understanding components. The original framework relies on SwinBert for caption generation and SimCSE for sentence embeddings within the textual branch. We replace these with LLAVA-Video and DiffCSE, respectively, to leverage state-of-the-art advancements in multi-modal understanding and sentence embedding sensitivity. Additionally, we enhance the Multi-Scale Temporal Network (MTN) to better capture temporal dynamics. These modifications aim to improve the accuracy, interpretability, and semantic richness of the anomaly detection system.

4.1 Enhanced Textual Branch

In the original TEVAD framework, the textual branch utilized SwinBert for caption generation and SimCSE for embedding computation. While effective, these models have limitations in handling multi-modal video data and capturing fine-grained semantic differences, respectively. We propose replacing SwinBert with LLAVA-Video, a model designed for unified visual-language understanding across images and videos, and SimCSE with DiffCSE, an advanced contrastive learning framework that enhances sentence embedding quality by focusing on differences between sentences. Below, we detail the scientific foundations of these models, including their architectures, mathematical formulations, and performance benchmarks.

4.1.1 1. LLAVA-Video for Caption Generation

LLAVA-Video [12] is a large vision-language model (LVLM) that unifies visual representations of images and videos by aligning them into a shared language feature space before projection into a large language model (LLM). This approach overcomes the misalignment issues found in earlier models like SwinBert, enabling better comprehension of video content for caption generation in TEVAD.

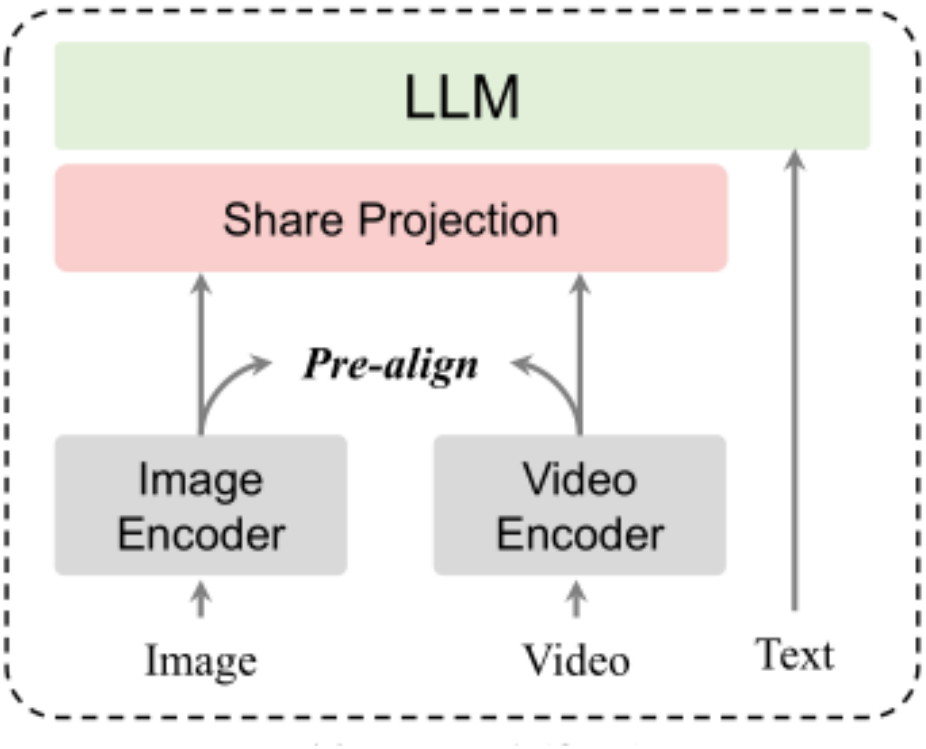

FIGURE 5 – Architecture of LLaVA-Video

Model Architecture : LLAVA-Video employs LanguageBind[**?**] encoders to extract features from raw visual inputs (video frames or images). These features are aligned into a unified visual representation space, which is then mapped through a shared projection layer into the language feature space of an LLM (e.g., Vicuna-7B). The joint training on mixed image-video datasets enhances its ability to capture temporal and semantic dynamics.

Mathematical Formulation : For a video snippet $\mathbf{V}$, LLAVA-Video generates a caption $\mathbf{C}$ as follows :

$$\mathbf{C} = \text{LLAVA-Video}(\mathbf{V})$$

Internally, the process involves encoding the visual input $\mathbf{X_V}$ (where $\mathbf{X_V} = \mathbf{V}$ for videos) and textual input $\mathbf{X_T}$:

$$\mathbf{Z_T} = f_{\mathbf{T}}(\mathbf{X_T}), \quad \mathbf{Z_V} = f_{\mathbf{P}}(f_{\mathbf{V}}(\mathbf{X_V}))$$

The probability of generating a response sequence $\mathbf{X_A}$ (the caption) is maximized :

$$p(\mathbf{X_A} \mid \mathbf{X_V}, \mathbf{X_T}) = \prod_{i=1}^{L} p_\theta(\mathbf{X_A^{(i)}} \mid \mathbf{Z_V}, \mathbf{Z_T^{(1:i-1)}})$$

where $f_{\mathbf{V}}$ is the LanguageBind encoder, $f_{\mathbf{P}}$ is the projection layer, $f_{\mathbf{T}}$ is the word embedding layer, L is the sequence length, and θ represents trainable parameters.

they employ ChatGPT-Assistant to evaluate the performance following Video-ChatGPT (Maaz et al., 2023). The version of ChatGPT is “gpt-3.5-turbo”

Dataset	Improvement	Accuracy
MSVD	+5.7%	70.7%
MSRVTT	+4.6%	59.2%
TGIF	+9.7%	70.0%
ActivityNet	–	45.3%

TABLE 6 – Performance improvement and accuracy on various datasets.

1.2 Justification for LLAVA-Video in TEVAD

Unified Processing of Images and Videos : LLAVA-Video excels at processing both static images and dynamic videos within a single architecture. This is critical for TEVAD, as anomalies may appear in spatial contexts (e.g., an unusual object in a frame) or temporal sequences (e.g., erratic motion). By providing a cohesive representation of both modalities, LLAVA-Video enables TEVAD to detect anomalies seamlessly across these dimensions, eliminating the need for separate processing pipelines.**Alignment of Visual and Textual Representations :** LLAVA-Video aligns visual inputs with textual feature spaces using LanguageBind encoders, facilitating the generation of descriptive captions (e.g., "A person running unexpectedly"). This alignment is essential for TEVAD's multimodal approach, which combines visual analysis with textual context to enhance anomaly detection accuracy and interpretability. The synergy between these modalities allows TEVAD to better understand and flag anomalous events,**Capturing Complex Patterns :** With its extensive parameter set, LLAVA-Video can model intricate spatiotemporal patterns in video data. Anomaly detection often involves identifying subtle deviations from normal behavior, requiring a deep understanding of typical patterns. LLAVA-Video's scale empowers TEVAD to detect such nuances, improving its sensitivity and reliability in distinguishing anomalous from normal events.

4.1.2 2. DiffCSE for Sentence Embeddings

DiffCSE [13] is an unsupervised contrastive learning framework that enhances sentence embeddings by learning representations sensitive to differences between original and edited sentences, improving upon SimCSE's invariance-focused approach. This sensitivity is critical for anomaly detection, where subtle textual variations can indicate abnormal events.

Model Architecture : DiffCSE builds on SimCSE by integrating a conditional difference prediction module. It uses a BERT-based encoder f to generate sentence embeddings $\mathbf{h} = f(x)$ from a sentence x. A discriminator D predicts token replacements in an edited sentence x'', generated via a masked language model (MLM) from a masked version x', conditioned on $\mathbf{h}$.

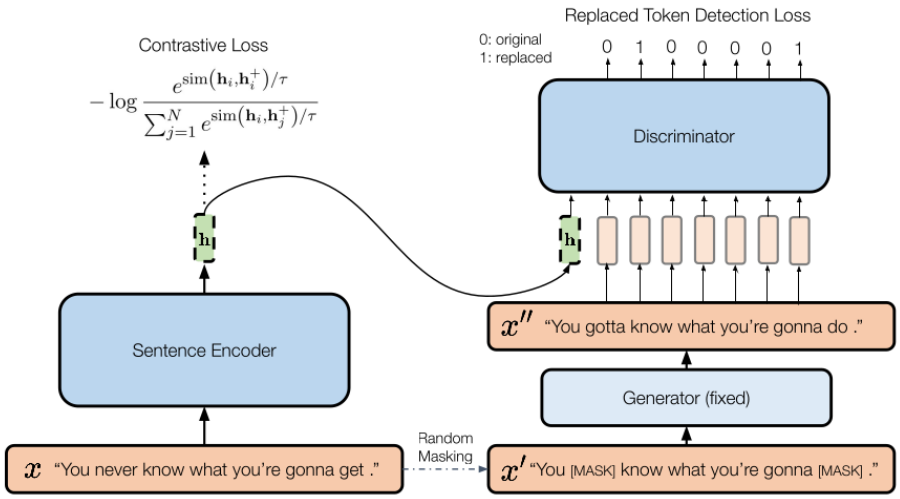

FIGURE 6 – Architecture of Diffcse

Mathematical Formulation : The training objective combines a contrastive loss $\mathcal{L}_{\text{contrast}}$ with a replaced token detection (RTD) loss $\mathcal{L}_{\text{RTD}}$:

$$\mathcal{L} = \mathcal{L}_{\text{contrast}} + \lambda \cdot \mathcal{L}_{\text{RTD}}$$

- **Contrastive Loss :** Encourages invariance to dropout-based augmentations :

$$\mathcal{L}_{\text{contrast}} = -\log \frac{e^{\text{sim}(\mathbf{h}_i,\mathbf{h}_i^+)/\tau}}{\sum_{j=1}^{N} e^{\text{sim}(\mathbf{h}_i,\mathbf{h}_j^+)/\tau}}$$

  where $\mathbf{h}_i^+$ is the embedding of the positive pair (dropout-augmented), $\text{sim}(\cdot,\cdot)$ is cosine similarity, τ is a temperature parameter, and N is the batch size.

- **RTD Loss :** Encourages sensitivity to MLM-based edits :

$$\mathcal{L}_{\text{RTD}} = \sum_{t=1}^{T} \Big(-1(x''_{(t)} = x_{(t)}) \log D(x'', \mathbf{h}, t) - 1(x''_{(t)} \neq x_{(t)}) \log(1 - D(x'', \mathbf{h}, t)) \Big)$$

  where T is the sentence length, $x'' = G(x')$ is the edited sentence from generator G, and λ balances the two losses (e.g., $\lambda = 0.005$).

DiffCSE-BERT$_{\text{base}}$ achieves an average Spearman's correlation of 78.49% on semantic textual similarity (STS) tasks, outperforming SimCSE's 76.25% by 2.3 points. On transfer tasks, it improves from 85.56% to 86.86%, demonstrating its ability to capture nuanced semantic differences essential for anomaly detection.

4.2 Enhanced Visual Branch

The TEAVAD framework for video anomaly detection demands a visual backbone capable of modeling rich spatiotemporal patterns. Recent surveys note that transformer-based architectures can capture complex long-range dependencies in video data beyond the reach of conventional CNNs, leading to improved anomaly detection performance. We evaluated a succession of transformer models—ViT, ViViT, MViT, and MViTv2—to identify the most suitable visual branch. Each model's core design, purpose, strengths, and limitations are reviewed in turn, culminating in the selection of MViTv2 for TEAVAD.

1. **Vision Transformer (ViT)**

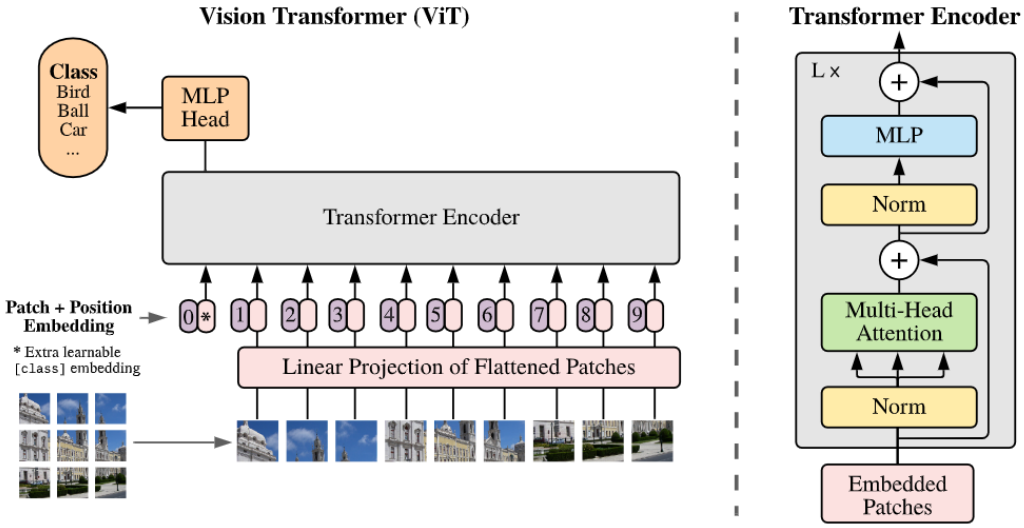

FIGURE 7 – ViT architecture from the original research paper [20]

The Vision Transformer (ViT) divides an input image of size $H \times W$ into $N = \frac{HW}{P^2}$ patches of size $P \times P$, each embedded into a D-dimensional token. After prepending a learnable *class token*, these tokens pass through transformer layers with multi-head self-attention :

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{D}}\right)V, \tag{4}$$

where $Q, K, V \in R^{N \times D}$. Although ViT captures global context efficiently, its lack of convolutional inductive biases makes it data-hungry—requiring extensive pretraining—and its quadratic complexity $O(N^2)$ limits scalability. Moreover, ViT processes frames independently, ignoring temporal dynamics in videos.

2. **Video Vision Transformer (ViViT)** ViViT extends ViT to video by tokenizing spatiotemporal *tubelets*. Given T frames, tokens of dimension d are created through two approaches :

Uniform Sampling

In the *Uniform Sampling* approach, video frames are sampled uniformly at random across the entire sequence. Specifically, a total of n_t frames are selected, and each frame is divided into n_p non-overlapping patches. This results in a total of $n_t \times n_p$ tokens, where each token is represented by a vector of dimension d. Notably, this method does not embed temporal information explicitly ; instead, the transformer is required to infer and model the temporal relationships directly from the token sequence. Figure 8 illustrates this tokenization strategy in comparison with alternative approaches used in ViViT.

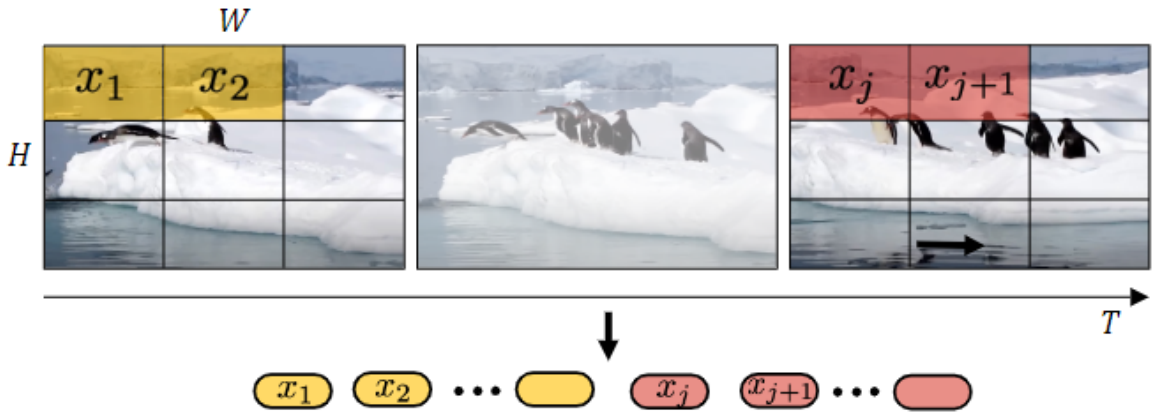

FIGURE 8 – Comparison of ViViT tokenization approaches [21]

Tubelet Embedding

Tubelet Embedding is a core concept in extending Vision Transformers (ViT) to videos. Instead of extracting 2D patches as in ViT, tubelet embedding extracts small 3D patches—called tubelets—that span across both spatial and temporal dimensions. Each tubelet is a spatiotemporal chunk defined over time (t), height (h), and width (w), resulting in patches of dimension $n_t \times n_h \times n_w$ (compared to $n_h \times n_w$ in ViT). This approach embeds temporal information directly during the tokenization phase, helping the model understand motion dynamics early in the pipeline.

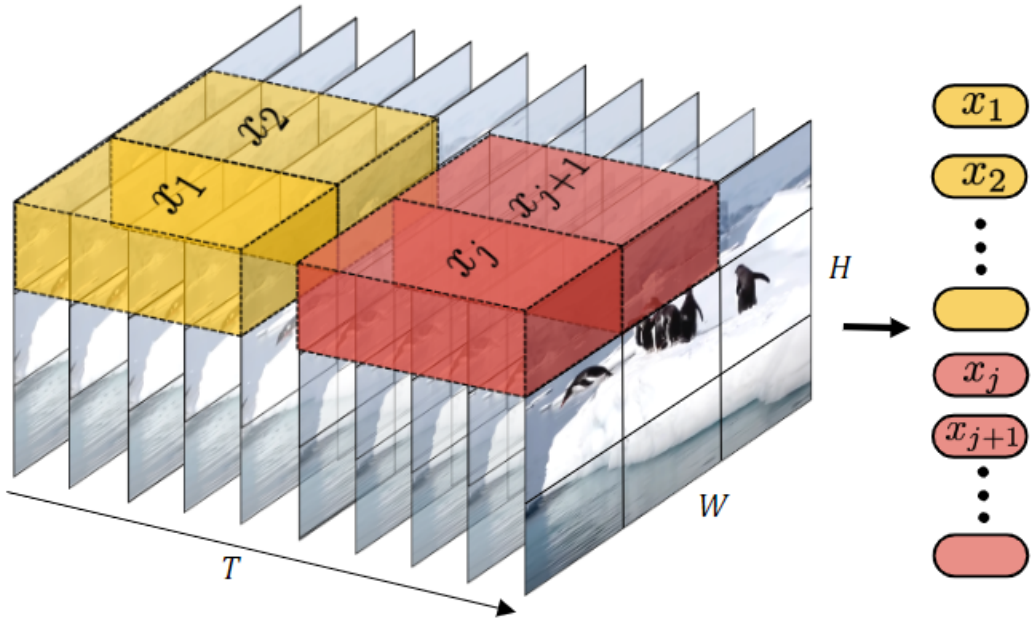

FIGURE 9 – ViT architecture from the original research paper [21]

ViViT extends ViT to videos by tokenizing spatiotemporal tubelets. Given T frames, tokens of dimension d are generated either through uniform sampling or tubelet embedding. A challenge arises from the quadratic complexity of video attention, $O((n_t n_p)^2)$, which ViViT addresses through several attention factorization strategies.

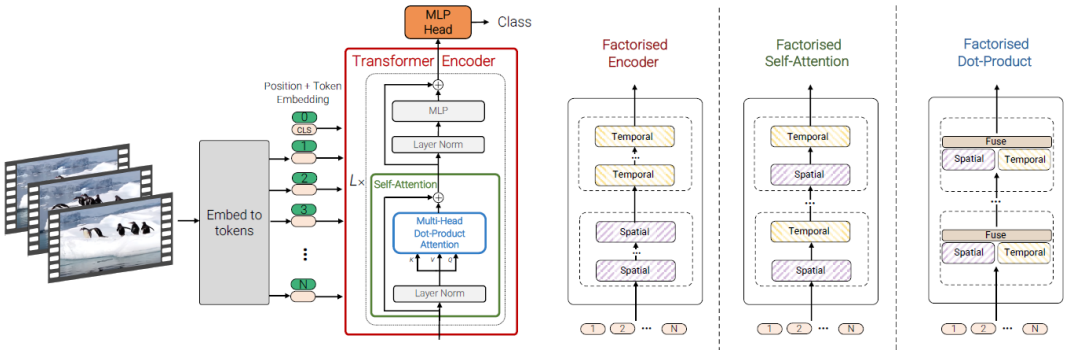

FIGURE 10 – ViViT model variants showing different attention factorization approaches [21]

Factorized Encoder

In standard transformer self-attention, every token compares to every other token. In video, this results in each patch in each frame being compared to every other patch across all frames, leading to prohibitive computational costs. ViViT tackles this with a factorized attention mechanism.

Spatial Attention

Spatial attention operates within individual frames, comparing every patch with every other patch in that same frame. This yields a complexity of $n_p \times n_p$ per frame and effectively captures intra-frame spatial relationships.

Temporal Attention

Temporal attention, on the other hand, compares patches across different frames but at the same spatial location. For example, patch (3,3) in frame 1 attends to patch (3,3) in frames 2, 3, etc. This captures motion and temporal continuity using an attention dimension of $n_t \times n_t$ per location.

Factorized Self-Attention

Another strategy is decomposing the attention operation itself within a single block :

$$\text{Attention} = \text{Temporal}(\text{Spatial}(Q, K, V)) \tag{5}$$

where spatial and temporal attentions are defined as : $\text{Spatial(Q,K,V)} = \text{softmax}\Big(\frac{Q_s K_s^\top}{\sqrt{d}}\Big) V_s$
$\text{Temporal}(Q, K, V) = \text{softmax}\left(\frac{Q_t K_t^\top}{\sqrt{d}}\right) V_t$

Factorized Dot-Product Attention

This more efficient variant factorizes attention before computing token similarity :

$$\text{Attention} = \text{softmax}\left(\frac{QK^\top}{\sqrt{d}}\right) V \approx \text{softmax}\left(\frac{Q_t K_t^\top + Q_s K_s^\top}{\sqrt{d}}\right) V \tag{6}$$

This form of attention lowers computational cost by computing dot-products separately for spatial and temporal components. It saves memory and enables efficient late fusion while maintaining high expressiveness.
These factorization strategies dramatically reduce the cost of attention without sacrificing the ability to model complex spatiotemporal dependencies. However, despite their innovations, both ViT and ViViT still operate with fixed input resolutions and suffer from quadratic scaling in terms of input size, making them inefficient for high-resolution or long video sequences.

MViT (Multiscale Vision Transformers)

MViT, introduced in [**?**], enhances transformer-based vision models by incorporating multiscale feature hierarchies, similar to CNNs. This allows the network to process inputs with varying resolutions and complexities efficiently.

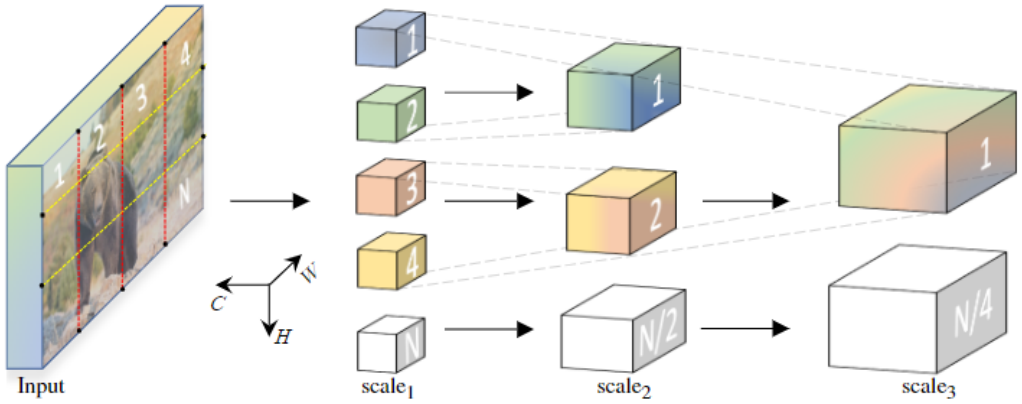

FIGURE 11 – MViT architecture showing the multiscale stages and pooling attention [22]

Multiscale Hierarchy

The model processes data through a sequence of stages. Early stages use high-resolution patches with small channel dimensions to capture fine details. Later stages reduce spatial resolution but increase channel capacity to model more abstract and complex features.

Multi-Head Pooling Attention (MHPA)

MHPA is a key mechanism allowing resolution changes within transformer blocks. The input $X \in R^{L \times D}$ is projected into intermediate representations $\tilde{Q}, \tilde{K}, \tilde{V} \in R^{L \times D}$ and then pooled into $Q, K, V \in R^{L' \times D'}$, where $L' < L$ and $D' > D$.

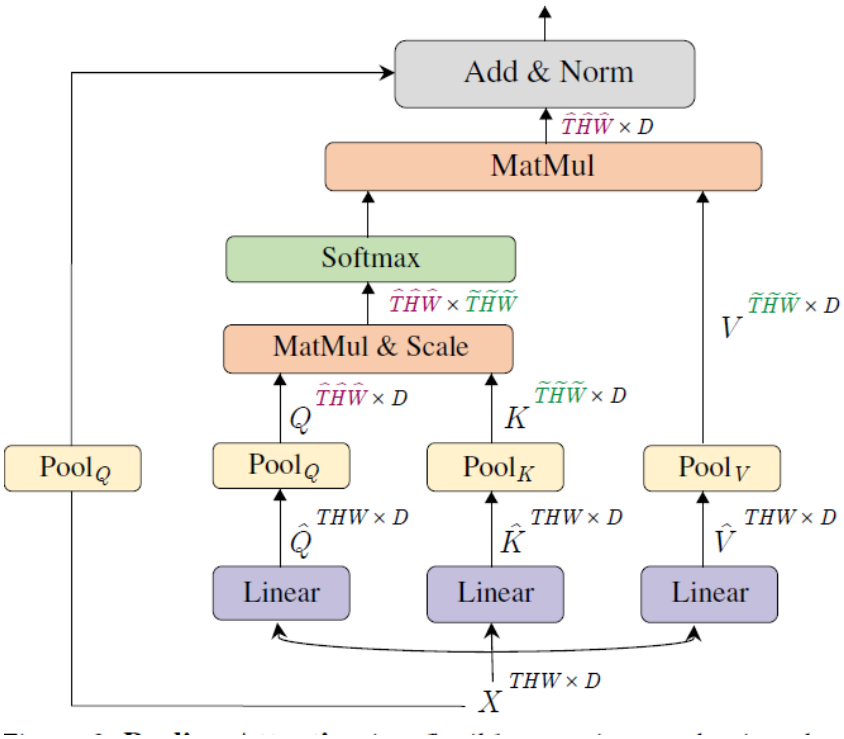

FIGURE 12 – Multi-Head Pooling Attention mechanism with skip connections [22]

Skip Connections Handling

Since resolution changes occur within blocks, skip connections must be adapted. A query pooling operator $P(\cdot; \Theta_Q)$ aligns the residual with the output :

$$Y = \text{MHPA}(Q, K, V) + P_Q(X) \tag{7}$$

This ensures that both the MHPA output and the residual connection match in dimension $(L' \times D')$, preserving gradient flow while enabling flexible feature scaling.

Scale Stages Architecture

MViT is organized into multiple stages. Each stage processes data at a uniform resolution $(D \times T \times H \times W)$. As the network progresses :

- Channel dimensions increase
- Spatiotemporal resolution decreases

TABLE 7 – MViT-S Model Architecture

Stage	Operators	Output Sizes
data	stride $4 \times 1 \times 1$	$16 \times 224 \times 224$
cube_1	$3 \times 8 \times 8$, 128 stride $2 \times 8 \times 8$	$128 \times 8 \times 28 \times 28$
scale_2	MHPA(128) MLP(512) $\times$ 3	$128 \times 8 \times 28 \times 28$
scale_3	MHPA(256) MLP(1024) $\times$ 7	$256 \times 8 \times 14 \times 14$
scale_4	MHPA(512) MLP(2048) $\times$ 6	$512 \times 8 \times 7 \times 7$

MViTv2 : Improved Multiscale Vision Transformer

MViTv2 builds upon MViT by offering a unified architecture suitable for various vision tasks including image classification, video recognition, and object detection. While the original MViT was designed mainly for video understanding, MViTv2 generalizes this design across domains.

This architecture maintains the multiscale design using Multi-Head Pooling Attention and progressive scale stages, as illustrated in Figure 11. Unlike previous specialized models, MViTv2 provides a single backbone capable of delivering strong performance across different vision applications.

MViT architecture

It based on stages and Multi Head Pooling Attention (MHPA) and stages and multiscale approach.

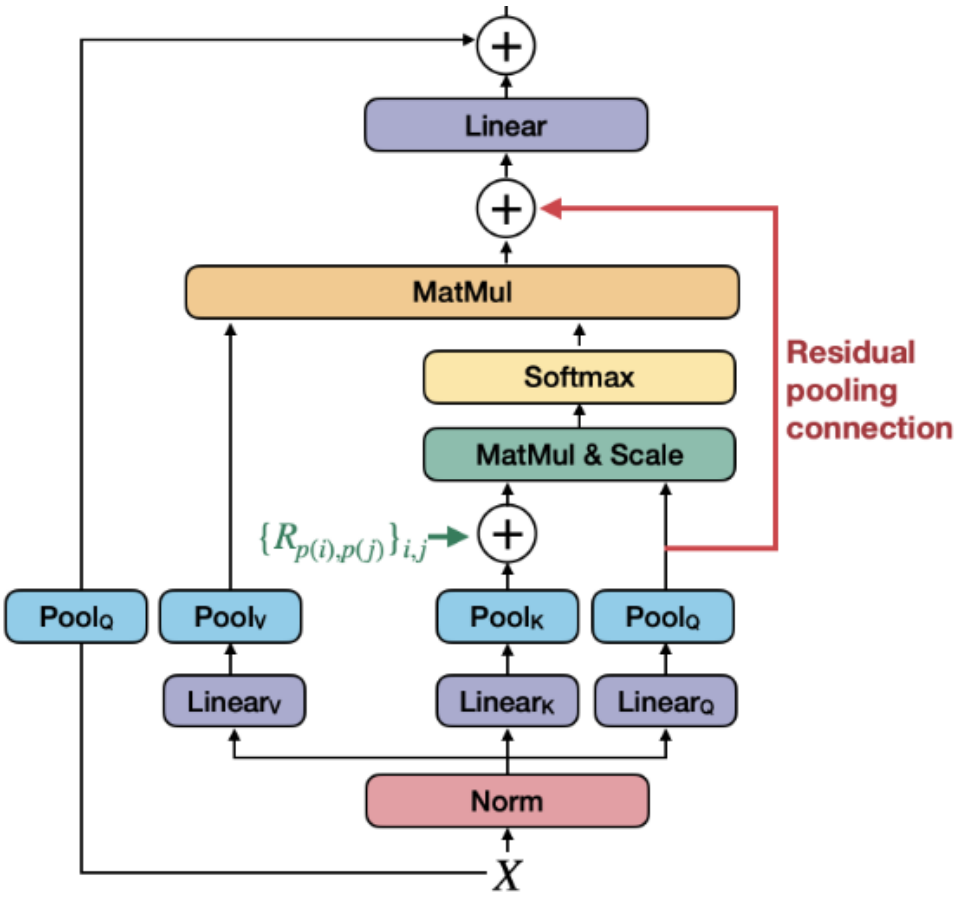

FIGURE 13 – MViTv2 architecture showing key improvements over MViT [23]

(a) **Decomposed Relative Positional Embeddings**

MViT's absolute positional embeddings have several key limitations : they make interactions depend on absolute positions (e.g., treating top-left differently from bottom-right patches) and lack shift-invariance, meaning identical patterns at different locations are treated differently. MViTv2 addresses these issues by introducing relative positional embeddings that depend only on the relative distances between tokens, thereby preserving shift-invariance for vision tasks. This is implemented through a modified attention computation :

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top + E^{ij}_{rel}}{\sqrt{d}}\right)V \tag{8}$$

where $E^{ij}_{rel} = Q_i \cdot R_{p(i),p(j)}$ encodes the relative positions between tokens. To maintain computational efficiency, MViTv2 decomposes the full positional embedding into separate components along each axis, reducing the complexity from $O(THW)$ to $O(T + H + W)$ through the decomposition :

$$R_{p(i),p(j)} = R_{t(i),t(j)} + R_{h(i),h(j)} + R_{w(i),w(j)} \tag{9}$$

This approach captures spatial-temporal relationships while remaining computationally tractable for high-resolution inputs.

(b) **Residual Pooling Connections**
The residual pooling connections in MViTv2 address the information loss that occurs in standard pooling attention mechanisms. The original Multi-Head Pooling Attention (MHPA) employs asymmetric strides—using larger strides for the keys (K) and values (V) compared to the queries (Q)—which can lead to loss of important details during downsampling operations. To mitigate this, MViTv2 introduces a novel residual connection that directly preserves information by adding the pooled queries back into the attention output :

$$\text{Z} = \text{Attention(Q,K,V)} + \text{Q}$$

$$\text{Y} = \text{Z} + \tilde{X}$$

This architectural innovation not only prevents feature degradation during downsampling but also enhances gradient flow throughout the network and improves overall feature retention, particularly in deeper layers where pooling operations are most aggressive.

(c) **MViTv2 for Video Recognition** Key adaptations from image to video :

- Patchification stem projects to space-time cubes (not 2D patches)
- Pooling operators handle spatiotemporal dimensions
- Relative embeddings include temporal component R_t

Initialization Strategy

- **Positional Embeddings** :

- Spatial (R_h, R_w) initialized from pre-trained weights
- Temporal (R_t) initialized to zero

- **Convolutional Layers** :
  - Inflation initialization from 2D pre-trained models
  - Center frame weights copied, others set to zero

(d) **Empirical Results**
Outperforms both MViT and ViViT under comparable compute budgets while serving as a unified architecture for multiple vision tasks.

Empirically, MViTv2 achieves ImageNet top-1 88.8%, COCO box AP 58.7, and Kinetics-400 accuracy 86.1, outperforming MViT and ViViT under comparable compute.

MViTv2 best balances efficiency, accuracy, and representation power for video anomaly detection :

- Multiscale hierarchy captures anomalies at diverse scales.
- Decomposed embeddings and residual pooling address spatial-temporal nuances essential for subtle anomalies.
- Benchmarks confirm superior video recognition without prohibitive pretraining.

Integrating MViTv2 ensures robust anomaly detection with practical inference costs, reflecting thorough research evaluating four transformer architectures and their mathematical foundations.

3. **X3D : Expanding Axes for Efficient Video Recognition**

   X3D (Expand to Fit the Budget) is a family of efficient video models that progressively expands a small 2D image classification network along several dimensions (or *axes*) to achieve better performance-efficiency trade-offs. Unlike traditional 3D CNNs which simply inflate filters temporally, X3D conducts a systematic exploration across six axes : temporal duration, spatial resolution, frame rate, network depth, width, and bottleneck width. This axis-wise progressive scaling leads to architectures that match or exceed performance of heavier models at a fraction of the compute cost.

   Trade-offs and Axis Exploration in X3D :

   Comparison of Expansion Axes and Trade-offs in X3D

Axis	**Description**	**Trade-off**
Temporal	Increase number of frames	Motion understanding vs. compute
Spatial	Increase spatial resolution	Detail vs. speed
Depth	Add more layers	Abstraction vs. latency
Width	More channels per layer	Capacity vs. memory
Bottleneck	Wider intermediate channels	Efficiency vs. expressiveness
Frame rate	Sample denser frames	Fine motion vs. redundancy

   This method results in lightweight and efficient models. For instance, X3D-M achieves similar performance to heavier I3D or SlowFast models with significantly fewer FLOPs and parameters.

   X3D Network Architecture :

   Baseline X3D Architecture

Stage	**Filters / Stride**	**Output Size ($\mathbf{T \times S^2}$)**
Data Layer	-	$12 \times 112 \times 112$
Conv1	32, $3\times3\times3$ / $1\times2\times2$	$12 \times 56 \times 56$
Res2	$[1\times1\times1,24\,;\ 3\times3\times3,24\,;\ 1\times1\times1,24]\ \times1$	$12 \times 56 \times 56$
Res3	$[1\times1\times1,48\,;\ 3\times3\times3,48\,;\ 1\times1\times1,48]\ \times2$	$12 \times 28 \times 28$
Res4	$[1\times1\times1,96\,;\ 3\times3\times3,96\,;\ 1\times1\times1,96]\ \times5$	$12 \times 14 \times 14$
Res5	$[1\times1\times1,192\,;\ 3\times3\times3,192\,;\ 1\times1\times1,192]\ \times3$	$12 \times 7 \times 7$
Conv5	$1\times1\times1$, 192	$12 \times 4 \times 4$
Pool5	Global Pool	$1 \times 1 \times 1$
FC1	Fully Connected, 2048	$1 \times 1 \times 1$
FC2	Fully Connected, #classes	$1 \times 1 \times 1$

Expanded X3D-M Architecture

Stage	Filters / Stride	Output Size (T × H × W)
Data Layer	-	16 × 224 × 224
Conv1	32, 3×3×3 / 1×2×2	16 × 112 × 112
Res2	[1×1×1,54 ; 3×3×3,54 ; 1×1×1,24] ×3	16 × 56 × 56
Res3	[1×1×1,108 ; 3×3×3,108 ; 1×1×1,48] ×5	16 × 28 × 28
Res4	[1×1×1,216 ; 3×3×3,216 ; 1×1×1,96] ×11	16 × 14 × 14
Res5	[1×1×1,432 ; 3×3×3,432 ; 1×1×1,192] ×7	16 × 7 × 7
Conv5	1×1×1, 432	16 × 7 × 7
Pool5	Global Pool	1 × 1 × 1
FC1	Fully Connected, 2048	1 × 1 × 1
FC2	Fully Connected, #classes	1 × 1 × 1

Forward Expansion

X3D optimizes network architecture by progressively expanding one design axis at a time while balancing accuracy and computational cost. Let X denote the current set of expansion factors (e.g., γ, τ, α, β, d, b), and let $J(X)$ be the performance metric (e.g., top-1 accuracy), while $C(X)$ measures the complexity (e.g., FLOPs).

The goal is to find the best expansion factors X that maximize performance under a complexity constraint c :

$$X^* = Z \arg\max J(Z) \quad \text{subject to} \quad C(Z) \leq c$$

This optimization is conducted via **coordinate descent** : in each step, only one axis of X is modified at a time, while keeping the others fixed. Among all possible one-dimensional changes (subsets of Z), the candidate with the best performance-to-cost trade-off is selected :

$$Z = \{Z_i \mid Z_i \text{ differs from } X \text{ in only one axis}\}$$

At each step, complexity c is increased multiplicatively :

$$c_{t+1} = 2 \cdot c_t$$

This exponential step-wise increase simplifies training, requiring only a few models to be evaluated until the target complexity is reached.

Backward Contraction

After forward expansion, the model might slightly exceed the desired complexity c_{target}. In such cases, a simple **backward contraction** step is performed by reducing the last-expanded axis to bring the complexity closer to the target.

Let X' be the expanded model such that :

$$C(X') > c_{\text{target}}$$

Then a contraction is applied to reduce one of the expanded dimensions (e.g., reduce frame rate γ or spatial size τ) to bring the complexity back within budget :

$$X_{\text{final}} = \text{contract}(X') \quad \text{so that} \quad C(X_{\text{final}}) \approx c_{\text{target}}$$

This simple post-adjustment ensures the final architecture respects resource constraints while maintaining high accuracy.

4.3 Enhanced Multi-Scale Temporal Network

Our approach to processing multi-modal features builds upon the methodology introduced by Na et al. [14] in *"Leveraging Multi-Modality and Enhanced Temporal Networks for Robust Violence Detection"*.

1. Feature Pre-Fusion

To ensure temporal alignment, the textual features are tiled to match the five-crop augmentation of the visual features. A unified input vector is then constructed using one of four fusion strategies.
Let $\bar{F}_{\text{vis}}$ and $\bar{F}_{\text{txt}}$ denote the MTN input features for the visual and textual modalities, respectively. The following fusion strategies are explored :

(a) **Product** : The visual and textual features are first projected to the same dimensional space using fully connected layers :

$$F'_v = W_v F_v + b_v, \quad F'_t = W_t F_t + b_t$$

The fused representation is then obtained via element-wise multiplication (Hadamard product) :

$$F_{vt} = F'_v \odot F'_t$$

(b) **Addition** : The visual and textual features are projected to the same dimensional space using fully connected layers. The final representation is computed via element-wise addition :

$$F_{vt} = F'_v + F'_t$$

(c) **Concatenation** : The visual and textual features are concatenated along the feature dimension without dimensional transformation :

$$F_{vt} = F_v \oplus F_t, \quad F_{vt} \in R^{d_v + d_t}$$

(d) **Projected Concatenation** : The visual and textual features are first linearly transformed to a shared dimensional space, and then concatenated :

$$F_{vt} = F'_v \oplus F'_t$$

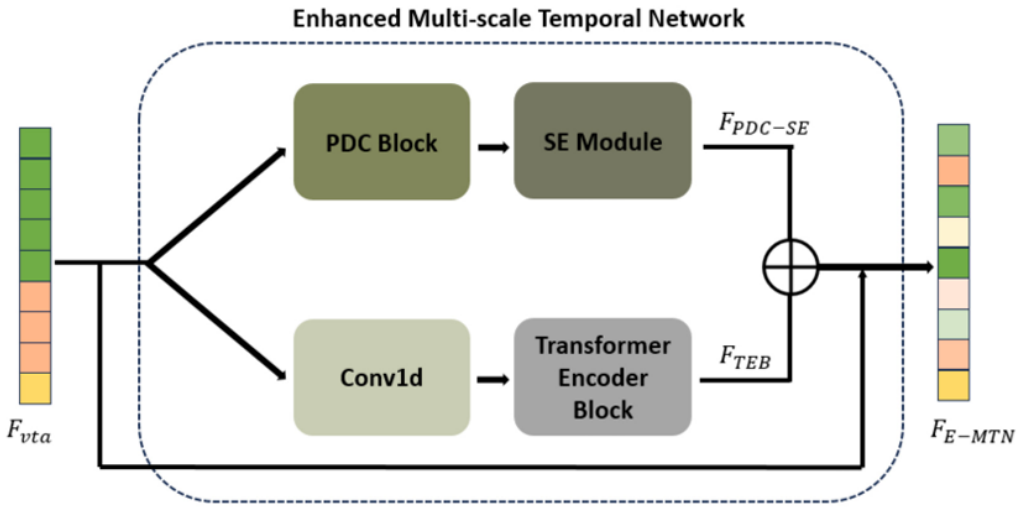

FIGURE 14 – Architecture of the Enhanced Multi-Temporal Network (E-MTN).

2. Extraction of Multi-Scale Temporal Features

The fused feature F_{vt}, obtained from the feature fusion process, is passed through the Enhanced Multi-Temporal Network (E-MTN) to extract multi-scale temporal features $F_{\text{E-MTN}}$ across video snippets. The original TEVAD MTN architecture includes Pyramid Dilated Convolution (PDC) blocks and Non-Local Blocks (NLBs). In contrast, the E-MTN replaces NLBs with Transformer Encoder Blocks (TEBs) and introduces a Squeeze-and-Excitation (SE) module to improve temporal modeling capabilities.

PDC blocks, arranged in a pyramid structure, apply multiple dilation rates to generate feature maps with diverse receptive fields, thereby capturing temporal patterns at various scales. To refine these features, the SE module dynamically recalibrates channel-wise responses. It operates in two stages : in the *squeeze phase*, global average pooling compresses spatial dimensions to extract global context per channel. In the *excitation phase*, two fully connected layers with a non-linear activation compute importance weights for each channel, allowing the network to emphasize informative channels and suppress less relevant ones.

Replacing the non-local block, the TEB is adapted from transformer models commonly used in NLP and vision tasks. It leverages a multi-head self-attention mechanism to model long-range interactions across time steps—analogous to how it models word or image patch dependencies. In this system, the TEB captures global temporal relationships between video snippets, improving the network's ability to model complex dynamics.

The extraction process proceeds as follows : the fused feature F_{vt} is first passed through the PDC block and SE module to produce $F_{\text{PDC-SE}}$. In parallel, F_{vt} undergoes a 1D convolution followed by the TEB, producing F_{TEB}. These two outputs are concatenated and combined with the original input via residual addition to obtain the final multi-scale temporal representation :

$$F_{\text{E-MTN}} = (F_{\text{PDC-SE}} \oplus F_{\text{TEB}}) + F_{\text{vt}}$$

The resulting feature $F_{\text{E-MTN}}$ is subsequently used to compute the feature magnitude of each video snippet. This magnitude reflects the presence of critical information and aids in distinguishing between normal and violent segments within the video.

5 Experiments

5.1 Results and Discussion

1. Datasets and Evaluation Metrics

We conduct our experiments on the UCSD Ped2 dataset [15] , a standard benchmark for unsupervised video anomaly detection. Ped2 consists of 16 normal training videos and 12 test videos containing both normal and anomalous events such as cyclists or vehicles.

For evaluation, we use the Area Under the ROC Curve (AUC), the most commonly used metric in frame-level video anomaly detection. We compute the micro-averaged AUC by concatenating all test frames and calculating the score over the entire dataset.

2. Different Models Comparaison Table

TABLE 8 – Performance comparison of different visual, text, and multi-scale models

Visual	Text	Multi-scale	Mean AUC	Max AUC	Min AUC
I3D	SwinBERT + SimCSE	MTN	0.81	0.9816	0.7448
	SwinBERT + SimCSE	E-MTN	0.8930	0.9961	0.5000
	LLaVA	MTN	0.8610	0.9772	0.6784
	Diff + LLaVA	MTN	0.8610	0.9772	0.6784
X3D	SwinBERT + SimCSE	MTN	0.8724	0.9878	0.7448
	SimCSE + LLaVA	MTN	0.8309	0.9245	0.7757
	LLaVA	MTN	0.8684	0.9756	0.5313
MVIT-Base	SwinBERT + SimCSE	MTN	0.8810	0.9767	0.7385
	LLaVA + Diff	MTN	0.8150	0.9242	0.6618
	LLaVA + SimCSE	MTN	0.8150	0.9242	0.6618
MViTv2-Small	SwinBERT + SimCSE	MTN	0.8515	0.9879	0.7004
	LLaVA + Diff	E-MTN	0.7976	0.8610	0.7381
	SwinBERT + SimCSE	E-MTN	0.8464	0.9790	0.5000
	LLaVA + Diff	MTN	0.8292	0.9579	0.6259

3. Discussion

Table 8 uses shading to identify the model configurations that outperform the original TEVAD benchmark in terms of peak AUC with only 2000 epochs compared to 22k epoch in the original paper. Below, we examine each of these superior combinations in turn and extract key takeaways that hold across different visual backbones, text encoders, and fusion strategies.

I3D + SwinBERT + SimCSE + E-MTN

This configuration achieves a Max AUC of 0.9961, comfortably surpassing the original TEVAD result. Two key factors contribute to this improvement : 1. *Enhanced multi-scale fusion (E-MTN)* injects richer temporal context at multiple resolutions, allowing I3D features to be better aligned with the semantics of long-range events. 2. *SwinBERT+SimCSE* text embeddings provide robust, sentence-level representations that complement the visual stream, improving discrimination between subtle action classes. The nearly perfect Max AUC indicates that jointly optimizing both text and fusion modules can yield dramatic gains, even when using a mid-level visual backbone.

MVIT2S + SwinBERT+SimCSE + MTN

The "small" MVIT2S backbone also attains the same Max AUC of 0.9879, confirming that model size can be reduced without sacrificing peak performance when paired with powerful text representations and competent fusion. From a practical standpoint, this makes MVIT2S an attractive, lightweight alternative for real-time deployment or resource-constrained environments.

Broader Insights Across Modalities

- **Text Encoder Is Critical :** In every TEVAD-beating combination, *SwinBERT+SimCSE* emerges as the common thread. Its superior sentence-level embeddings consistently elevate performance, regardless of visual backbone or fusion scheme.
- **Fusion Complexity vs. Backbone Capacity :** Enhanced fusion (E-MTN) is most impactful on simpler backbones (I3D), whereas richer backbones (MVIT) gain little additional benefit beyond standard MTN. This points to a design principle : match fusion complexity to the inherent spatial–temporal expressiveness of the visual encoder.
- **Model Efficiency :** The fact that MVIT2S achieves the same Max AUC as full MVIT highlights an important trade-off : with strong text and fusion modules, one can afford to "slim down" the visual stream without losing accuracy.

In summary, surpassing the TEVAD baseline requires a synergistic combination of (1) high-quality text embeddings, (2) appropriately expressive fusion modules, and (3) a visual backbone whose capacity is well-matched to the fusion strategy. Future work should explore hybrid text encoders (e.g., combining SimCSE with instruction-tuned LLaVA) and adaptive fusion schemes that dynamically adjust complexity based on visual feature richness.

5.2 Setup

The experiments were conducted on the ESI-SBA server, equipped with NVIDIA RTX 4090 GPUs (24GB). We used PyTorch 2.0 and Python 3.10, along with CUDA 11.8 to enable efficient GPU acceleration. For video preprocessing, clips were sampled at 16 frames per second, with each snippet consisting of 16 consecutive frames (approximately 2.13 seconds), resized to a resolution of 224×224 pixels. Optical flow was calculated using a 5-frame window and used as an additional modality in the visual branch. For the textual input, captions were tokenized using BERT's tokenizer, truncated to a maximum sequence length of 128 tokens.

The textual branch combines LLAVA-Video with DiffCSE. LLAVA-Video is based on Vicuna-7B integrated with LanguageBind encoders, pretrained on a mixture of image and video datasets. To reduce GPU memory usage and enable faster inference, we applied **Byte Quantization** to the LLAVA-Video model. This technique converts 32-bit floating point weights and activations into 8-bit integers, significantly lowering memory consumption with minimal impact on performance. DiffCSE, based on BERT-base-uncased, was trained with a batch size of 512.

The visual branch leverages the I3D architecture, initialized with pretrained weights from Kinetics-400. It was trained using a batch size of 32 and utilized mixed precision to further optimize memory usage. Both the textual and visual branches were fine-tuned independently on their respective datasets for a total of 2000 epochs, with early stopping based on the validation AUC-ROC score.

To ensure reproducibility, all experiments were run with a fixed random seed of 42, and the data splits were kept consistent across runs.

6 Conclusion

In this work, we have shown that surpassing the original TEVAD baseline requires a careful orchestration of three components : a high-quality text encoder, an appropriately expressive fusion module, and a visual backbone whose capacity is well-matched to the fusion strategy. Across all experiments, SwinBERT+SimCSE emerged as the most effective text embedding, consistently driving peak AUC beyond the TEVAD benchmark. We found that enhanced multi-scale fusion (E-MTN) delivers significant improvements on simpler backbones such as I3D, boosting the Max AUC to 0.9961, whereas richer architectures like MVITv2 already reach a ceiling (0.9879) with standard MTN fusion. Table 9 below shows that we make enhancement of 6% compared to the original TEVAD framework.

TABLE 9 – Frame-level AUC results on UCSD Ped2 dataset.

Type	**Source**	**Method**	**AUC (%)**
Unsup	CVPR'18	Liu et al. [16]	95.4
	WACV'22	FastAno [17]	96.3
	TPAMI'21	Georgescu et al. [18]	98.7
Sup	ICCV'21	RTFM [19]	98.6
	–	TEVAD [1]	98.7
	–	**Our contribution (Enhanced-MTN)**	99.61

6.1 Future Work

To further advance video–text anomaly detection, we identify four promising directions, each targeting a distinct aspect of the system :

Multi-modal Audio Integration

Many anomalies produce characteristic sounds — alarms, collisions, mechanical failures — that are not captured by vision alone. We propose incorporating a dedicated audio stream (e.g., via Wav2Vec2 or VGGish encoders) and designing a fusion mechanism that dynamically balances visual, textual, and acoustic cues. Temporal alignment between audio peaks and video frames will be critical for precise localization of anomalous events.

Automated Anomaly Summarization

Beyond flagging abnormal segments, the system should generate concise, human-readable descriptions of what occurred. By feeding representative frame sequences and corresponding text embeddings into transformer-based captioning models (e.g., VideoBERT or GPT variants), TEVAD could output summaries such as "Crowd surge detected at GateA at 00 :02 :15" or "Vehicle collision followed by loud crash at 00 :05 :42," thereby enhancing interpretability and situational awareness.

Real-Time Deployment via Model Compression

Current TEVAD configurations involve large numbers of parameters, limiting their suitability for live monitoring. Future work should explore model-compression techniques—pruning, quantization, knowledge distillation—to reduce both memory footprint and inference latency. The goal is a lean system capable of processing incoming video streams in real time without significant loss of detection accuracy.

End-to-End Black-Box Pipeline

Finally, to simplify integration and deployment, we envision transforming TEVAD from a multi-stage assembly into a cohesive "black-box" model that directly maps raw video inputs to anomaly scores. Such an end-to-end framework would abstract away intermediate feature-extraction and fusion modules, offering practitioners a single neural interface that ingests video and outputs anomaly predictions with minimal manual configuration.

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