

Cognitive Attack Detection in Augmented Reality (CADAR): A Neuro-Symbolic Approach with Particle Filtering on Perception Graphs

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Abstract

Augmented Reality (AR) enriches human perception by overlaying virtual elements onto the physical world. However, this tight coupling between virtual and real content makes AR vulnerable to cognitive attacks: manipulations that distort users' semantic understanding of the environment. Existing detection methods largely focus on visual inconsistencies at the pixel or image level, offering limited semantic reasoning or interpretability. To address these limitations, we introduce CADAR, a neuro-symbolic framework for cognitive attack detection in AR that integrates neural and symbolic reasoning. CADAR fuses multimodal vision-language representations from pre-trained models into a perception graph that captures objects, relations, and temporal contextual salience. Building on this structure, a particle-filter-based statistical reasoning module infers anomalies in semantic dynamics to reveal cognitive attacks. This combination provides both the adaptability of modern vision-language models and the interpretability of probabilistic symbolic reasoning. Preliminary experiments on an AR cognitive-attack dataset demonstrate consistent advantages over existing approaches, highlighting the potential of neuro-symbolic methods for robust and interpretable AR security.

1. Introduction

Augmented Reality (AR) and Mixed Reality (MR) technologies increasingly overlay virtual content onto the physical world, reshaping how users perceive and interact with their surroundings [29]. This tight integration creates new vulnerabilities, as users tend to trust overlaid visual and spatial cues. Adversaries can exploit this trust to launch cognitive attacks, where malicious virtual content is injected or altered to mislead, distract, or manipulate users without

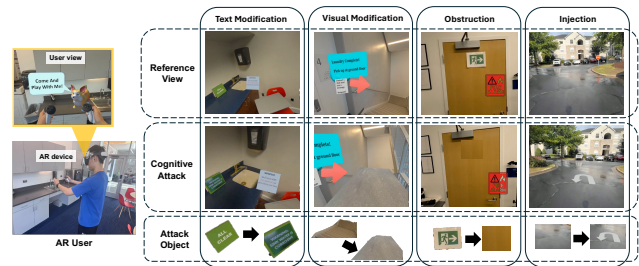


Figure 1. Illustrative AR/MR cognitive attacks. Top row: original scenes; bottom row: manipulated scenes. (a) Text Modification Attack. (b) Visual Modification attack. (c) Obstruction Attack. (d) Injection Attack.

their awareness [8, 22, 25, 26]. Unlike traditional cybersecurity threats that target system integrity, cognitive attacks operate at the perceptual level, subtly manipulating users' semantic understanding of a scene (examples in Fig.1).

Prior work on detecting anomaly and attacks often employs computer vision techniques to identify visual changes or adversarial distortions [1, 11, 12, 15, 18, 19, 24]. However, these methods rely on pixel/image processing, lacking the ability to model the human perception process that not only involves prior knowledge and contextual information, but also selectively focuses on aspects of the visual field for semantical interpretation. As a result, these methods may struggle to capture smart cognitive attacks manipulating only a small number of pixels and also may suffer from false positives due to benign visual perturbations that do not affect users' semantic interpretation [15]. More recent studies propose pre-trained vision-language models (VLMs) [20, 26] can achieve semantic-level detection by processing visual features and incorporating human-like knowledge. But the reasoning of pre-trained VLMs is a black-box approach offering limited interpretability. It is difficult to leverage domain-specific knowledge or model scene/context evolutions or temporal correlations in cognitive attack detection.

In this paper, we consider cognitive attacks that aim to manipulate users' semantic perception in AR/MR. We pro-

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pose *CADAR* (Cognitive Attack Detection in Augmented Reality), a neuro-symbolic approach encompassing two key components: (i) a symbolic perception-graph model, inspired by knowledge and scene graphs [5, 13, 21, 27]. It is extracted using pre-trained neural VLM models to represent scene/context evolution at the semantic-level, and (ii) a particle-filter model, which is commonly used in non-linear and stochastic systems. It applies a sequential Monte Carlo method to the perception graph for reasoning and detecting cognitive attacks, stabilizes inherently noisy or inconsistent VLM outputs, and mitigates errors or missed detections through probabilistic fusion. It also offers granular, flexible temporal detection, using reference sequences, frame-wise inference localizes attacks per frame, to produce a variable number of labels when needed. Thus, the *CADAR* approach inherits the adaptability of the pre-trained VLM (neural part), as well as the interpretability and reasoning rigor of particle filtering (symbolic part). It semantically interprets and models the sequential scene changes for robust cognitive attack detection in AR/MR, overcoming existing work’s limitations.

We summarize our contributions as follows:

- **Neuro-symbolic framework.** We introduce a hybrid architecture that converts VLM outputs into symbolic perception graphs for explicit and interpretable reasoning in AR cognitive attack detection.
- **Perception graph schema.** We design a spatio-temporal graph representation that integrates multimodal information from image/text encoders and detection modules to capture scene evolution.
- **Particle-filter reasoning.** We apply particle filtering to symbolic perception graphs, improving robustness to noisy VLM outputs and enabling principled statistical anomaly detection.
- **CADAR-50K dataset.** We build the AR cognitive attack dataset CADAR-50K, and demonstrate that *CADAR* achieves 74.6% accuracy, significantly outperforming all baseline methods.

2. Related Work

Cognitive Attacks in AR/MR. One well-studied category of visual attacks is adversarial attacks, which introduce imperceptible yet malicious perturbations to input data to mislead machine learning models [16, 28]. In contrast, cognitive attacks target perception-level semantics and aim to alter a human user’s understanding of a scene [8, 25]. Augmented Reality (AR) systems, which overlay virtual content onto the physical world to enhance perception and decision-making, are particularly vulnerable to such attacks. However, research on cognitive attacks in AR remains limited. Existing methods often rely on access to the original, unaltered scene for comparison or employ pre-trained VLMs with limited interpretability.

Neuro-symbolic Methods. Neuro-symbolic approaches couple deep neural networks with symbolic reasoning—i.e., reasoning over explicitly represented knowledge in formal languages, to capitalize on the complementary strengths of subsymbolic pattern recognition and symbolic compositionality [4, 17]. Within knowledge-graph research, most neuro-symbolic work addresses link prediction or graph completion, where the hybrid models offer interpretable rules, guided learning, and more transparent decision pathways [10]. Yet, like standard supervised techniques, many of these solutions still demand sizable labeled datasets. In contrast, our framework introduces a neuro-symbolic reasoning module that combines explicitly encoded rules with statistics, achieving high interpretability while remaining data-efficient.

Particle Filter and Statistical Reasoning. Particle filter is a sequential Monte Carlo algorithms for recursive Bayesian estimation [7], it propagates a set of weighted samples to approximate the posterior state distribution, outperforming classical Kalman filters in strongly non-linear or non-Gaussian settings [6, 14]. They are widely used in surveillance, robotics, and navigation, leveraging visual, geometric, and motion cues such as color, texture, and shape [3]. In *CADAR*, we model graph nodes and edges as stochastic particles, enabling robust reasoning under noisy or inconsistent VLM outputs.

3. Methodology

In this section, we define the four types of cognitive attacks in AR scenes and introduce our neuro-symbolic framework for detecting such attacks. As illustrated in Fig. 2, the framework consists of two main components: the perception graph model and the particle filter-based detection module. The perception graph encodes each frame as a 3D spatiotemporal structure, where nodes represent objects and edges capture their relationships across time (Fig. 3). These structured graphs are then passed into the attack detection algorithm (Fig. 4), which reasons over the particle filter to identify cognitive attacks.

3.1. Cognitive Attacks

We investigate four representative cognitive attack types that deliberately compromise the semantic integrity of AR scenes (Fig. 1). The text-modification attack manipulates on-scene text—such as changing “NO PARKING” to “FREE PARKING”—to reverse intended meanings or inject false instructions, thereby deceiving both human users and perception systems. The visual-modification attack distorts object appearance or placement—for example, turning a green light to red or relocating a stop sign—leading to recognition errors and misinformed user decisions. The obstruction attack targets critical information by occluding or deleting es-

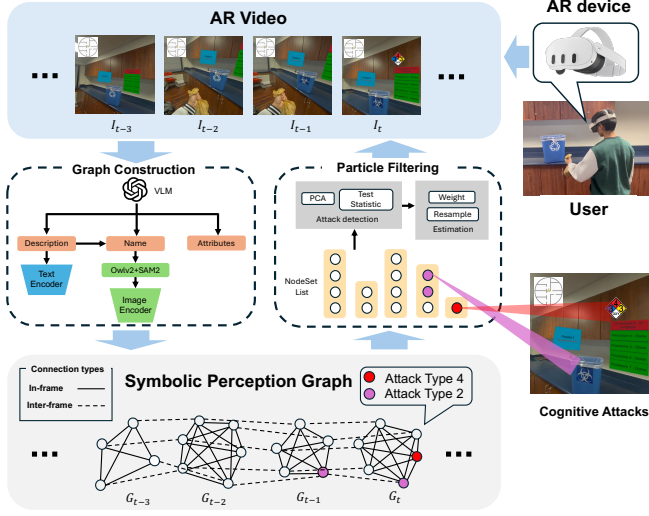


Figure 2. A system overview of CADAR. Sequential video frames are first transformed into spatial-temporal symbolic perception graphs. The attack-detection module then analyzes these graphs to identify, classify, and localize adversarial attacks, such as the visual modification and injection attacks shown in the examples.

sential cues like exit signs, disrupting safety awareness and expected graph relations. Finally, the injection attack introduces fictitious elements, such as fake hazard symbols or virtual labels, that embed misleading cues, divert user attention, and corrupt subsequent reasoning processes.

3.2. Perception Graph Model

The perception graph model is a symbolic representation of perception, simulating how humans perceive, interpret, and prioritize information. It collects, structures, and stores scene data that enables formal reasoning later. The graph leverages pre-trained VLMs to approximate human interpretation of sensory input. Given AR imagery and task context, the model fuses multimodal signals into a compact graph and embeds their semantics in a latent perceptual space.

A perception graph consists of nodes and edges. Objects are represented as nodes, and object relationships are represented as edges. Given the context information and prompt (shown in the Fig.3), the VLM would extract the related objects with their relationships in the scene. At timestep t , the Perception Graph G_t is generated as follows.

3.2.1. Graph Construction.

At discrete timestep $t \in \{1, \dots, T\}$ we ingest

$$I_t \in \mathbb{R}^{H \times W \times 3}, \quad c_t \in \mathcal{C}, \quad (1)$$

where I_t is the AR video frame and c_t encodes task context. A pre-trained vision-language module $\mathcal{F}_{\text{VLM}}$ lifts the frame into a spatio-temporal perception graph

$$G_t = (\mathcal{V}_t, \mathcal{E}_t) = \mathcal{F}_{\text{VLM}}(I_t, c_t), \quad (2)$$

with nodes $\mathcal{V}_t$ and edges $\mathcal{E}_t$:

$$\mathcal{V}_t = \{v_i^t\}_{i=1}^{N_t}, \quad \mathcal{E}_t = \{e_{ij}^t \mid v_i^t, v_j^t \in \mathcal{V}_t\}. \quad (3)$$

For reasoning that needs the *entire* observation history (e.g. long-range causal inference) we define GraphSet

$$\hat{G}_t = (\mathcal{V}_{1:t}, \mathcal{E}_{1:t}), \quad \mathcal{V}_{1:t} = \bigcup_{s=1}^t \mathcal{V}_s, \quad \mathcal{E}_{1:t} = \bigcup_{s=1}^t \mathcal{E}_s. \quad (4)$$

Thus, the GraphSet $\hat{G}_t$ is the union of all spatial and temporal connections that stitch object instances across time steps $1:t$. Each node still carries its original timestamp to preserve the temporal ordering.

Each node in the perception graph is represented by several attributes, including its ID, attack type, and timestep, along with a semantic description, visual features such as segmentation masks, a recognition probability score, contextual importance based on task relevance, and a reasonability score ranging from -3 to $+3$. These attributes are encoded using pre-trained vision-language and segmentation models to capture multimodal object representations. Each edge connects two nodes and includes similar parameters (node IDs, attack type, and timestep), along with a textual description capturing semantic, functional, navigational, or instructional relationships. Edge importance is derived from the contextual salience of the connected nodes.

3.2.2. NodeSet and EdgeSet.

After defining the temporal graph structure $\hat{G}_t$, which links perception graphs across time, we introduce the NodeSet and EdgeSet to represent the temporally connected nodes and edges, respectively.

At each time step t , the NodeSet for object i is denoted as $\mathcal{N}_{i,t}$, and the collection of all such NodeSets is represented as the NodeSet List $\mathcal{N}_t$.

$$\begin{aligned} \mathcal{N}_{i,t} &= \{v_i^k \mid 1 \leq k \leq t\}, \quad i \in \mathcal{I}_t, \\ \mathcal{N}_t &= \{\mathcal{N}_{i,t} \mid i \in \mathcal{I}_t\}. \end{aligned} \quad (5)$$

where $\mathcal{I}_t = \bigcup_{s=1}^t \{i \mid v_i^s \in \mathcal{V}_s\}$ is the set of all object IDs observed so far.

Similarly, EdgeSet and EdgeSet List is defined as:

$$\begin{aligned} E_{ij,t} &= \{e_{ij}^k \mid 1 \leq k \leq t\}, \quad i, j \in \mathcal{I}_t, \\ E_t &= \{E_{ij,t} \mid i, j \in \mathcal{I}_t\}. \end{aligned} \quad (6)$$

Thus the GraphSet $\hat{G}_t$ can also be represented by NodeSet and EdgeSet:

$$\hat{G}_t = (\mathcal{V}_{1:t}, \mathcal{E}_{1:t}), \quad \mathcal{V}_{1:t} = \bigcup_{i \in \mathcal{I}_t} \mathcal{N}_{i,t}, \quad \mathcal{E}_{1:t} = \bigcup_{i,j \in \mathcal{I}_t} E_{ij,t}. \quad (7)$$

3.3. Particle Filter Model

Our particle filter model tracks graph evolution and analyzes adversarial perturbations. It proceeds in three stages:

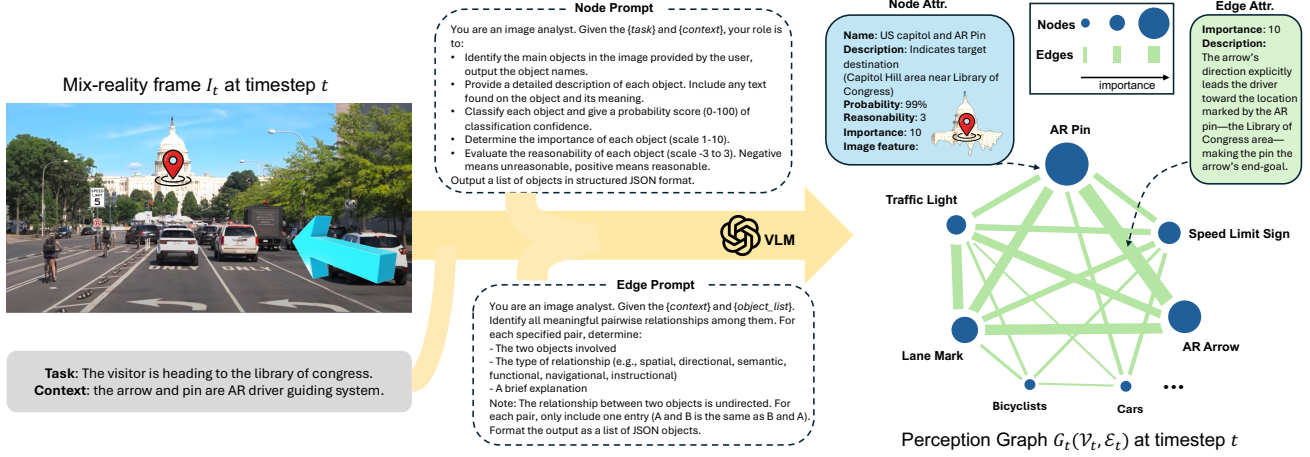


Figure 3. Symbolic perception graph generation: given a video frame and its contextual description, VLMs generate the corresponding perception graph at time step t .

prediction and matching, attack detection, and state estimation (Fig. 4). Each entity (node or edge) is treated as a particle. At each timestep, particles match the incoming observations with prior particles. The attack detection algorithm applies statistical tests to newly matched particles and discards those marked as attacked. Finally, weighting, resampling, and estimation produce an updated, temporally consistent graph state, preserving persistent NodeSet/EdgeSet identities and the relational structure over time.

3.3.1. Prediction and Matching.

To maintain persistent object identities across frames, we equip the NodeSet with the Prediction-Matching algorithm and use it to decide whether a newly detected Node belongs to an existing object list or creates a new one.

For any node v_i^t we denote $\mathbf{n}(v) =$ name embedding, $\mathbf{d}(v) =$ description embedding, $\mathbf{f}(v) =$ visual feature embedding, all $\in \mathbb{R}^{d_m}$. Cosine similarity for modality $m \in \{n, d, f\}$ is defined as $\text{sim}_m(u, v)$.

Let $\mathcal{A}_{t-1}$ be the set of NodeSet IDs that are still active at time $t - 1$. Each set maintains an Active Level $A_i^t \in [0, 3]$ (initialized to 3) indicating recent presence: if unmatched at time t , $A_i^t \leftarrow \max(0, A_i^{t-1} - 1)$; if matched, $A_i^t \leftarrow \min(3, A_i^{t-1} + 1)$. When $A_i^t = 0$, the node is considered absent and ceases matching. For every active object ID $i \in \mathcal{A}_{t-1}$ and each modality $m \in \{n, d, f\}$ compute the mean and standard deviation of pairwise similarities inside the NodeSet:

$$\mu_{i,m}^{t-1} = \frac{2}{|\mathcal{N}_{i,t-1}|(|\mathcal{N}_{i,t-1}| - 1)} \sum_{\substack{p < q \\ v_i^p, v_i^q \in \mathcal{N}_{i,t-1}}} \text{sim}_m(v_i^p, v_i^q),$$

$$\sigma_{i,m}^{t-1} = \text{StdDev}\{\text{sim}_m(v_i^p, v_i^q) \mid p < q, v_i^p, v_i^q \in \mathcal{N}_{i,t-1}\}. \quad (8)$$

To match the observed node to NodeSet, given a fresh node v_j^t and a candidate NodeSet i , define

$$s_{j,i,m} = \frac{1}{|\mathcal{N}_{i,t-1}|} \sum_{v \in \mathcal{N}_{i,t-1}} \text{sim}_m(v_j^t, v), \quad m \in \{n, d, f\}. \quad (9)$$

Candidate filter ($\leq 1\text{std}$ in every modality):

$$\mathcal{C}_j = \left\{ i \in \mathcal{A}_{t-1} \mid |s_{j,i,m} - \mu_{i,m}^{t-1}| \leq \sigma_{i,m}^{t-1}, \forall m \in \{n, d, f\} \right\}. \quad (10)$$

Finally, the assignment rule based on measuring the remaining candidate distance:

$$\mu_t(v_{j,t}) = \begin{cases} \arg \min_{i \in \mathcal{C}_j} \sum_{m \in \{n, d, f\}} |s_{j,i,m} - \mu_{i,m}^{t-1}|, & \mathcal{C}_j \neq \emptyset, \\ \text{new_id}, & \mathcal{C}_j = \emptyset. \end{cases} \quad (11)$$

If $\mu_t(v_j^t)$ returns an existing ID, append v_j^t to that NodeSet and update A_i^t ; otherwise, spawn a new NodeSet. Confirmed edges e_{ab}^t are then inserted into $E_{\mu_t(a)\mu_t(b),t}$ as before. After matching, the NodeSet goes into the Attack detection process.

3.3.2. Attack Detection.

To detect text (Type 1) and visual (Type 2) modification attacks, those that manifest as anomalies in embedding space, we employ a dedicated statistical procedure. Because the same description embeddings are later reused when assessing EdgeSets, we illustrate the method with the NodeSet case; the extension to edges is entirely analogous. A NodeSet with a fresh match in frame t is denoted $\mathcal{N}_{i,t} = \mathcal{N}_{i,t-1} \cup \{v_i^t\}$. Let $\tilde{\mathcal{N}}_{i,t-1} \subseteq \mathcal{N}_{i,t-1}$ be the subset of nodes that *have not* been flagged as attacks in earlier frames; these constitute the “clean” reference set.

For each modality $m \in \{d, f\}$ (description embedding, visual feature embedding), we use the Principal Component Analysis (PCA) to project it to a low-dimensional space, which removes noisy, low-variance directions. A PCA mapping on the clean reference data is computed by

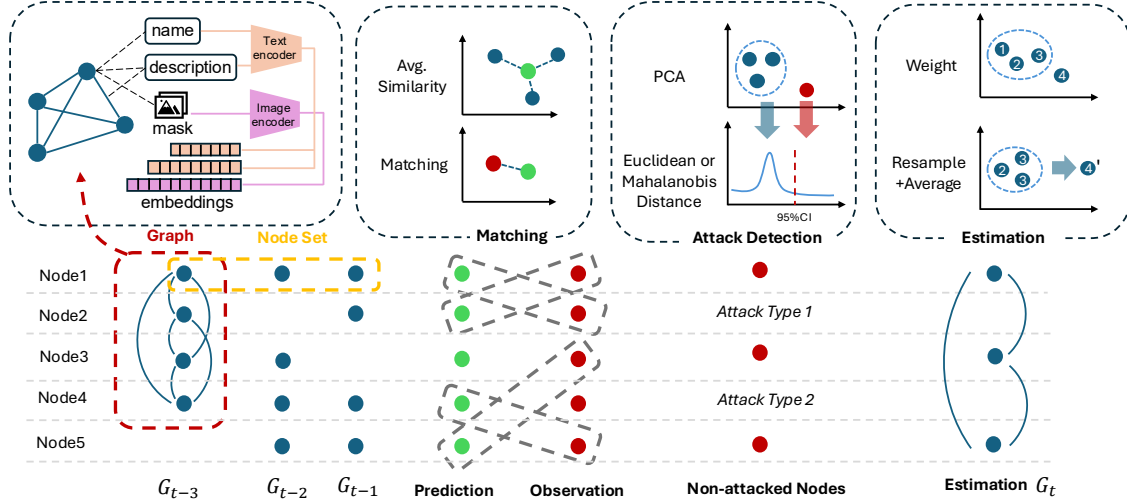


Figure 4. The particle filter-based attack detection framework consists of three main modules: matching, attack detection, and state estimation.

$$\mathbf{W}_{i,m}^{t-1} = \text{PCA}(\{\mathbf{m}(v)\}_{v \in \mathcal{N}_{i,t-1}}, k_m), \quad (12)$$

where k_m is chosen such that $\geq 99\%$ variance is retained. the resulting embeddings are modeled as Gaussian distributions:

$$\mathbf{z}_m(v) = \mathbf{W}_{i,m}^{t-1 \top} \mathbf{m}(v) \sim \mathcal{N}(\mathbf{c}_{i,m}^{t-1}, \Sigma_{i,m}^{t-1}) \quad (13)$$

with the centroid and covariance of PCA-reduced embeddings

$$\mathbf{c}_{i,m}^{t-1} = \frac{1}{|\tilde{\mathcal{N}}_{i,t-1}|} \sum_{v \in \tilde{\mathcal{N}}_{i,t-1}} \mathbf{z}_m(v), \quad \Sigma_{i,m}^{t-1} = \text{Cov}\{\mathbf{z}_m(v)\}. \quad (14)$$

Use the Mahalanobis distance for measuring Text and Visual Modification attack. For a new node v_i^t compute

$$\mathcal{M}_{i,t}^{(m)} = (\mathbf{z}_m(v_i^t) - \mathbf{c}_{i,m}^{t-1})^\top (\Sigma_{i,m}^{t-1})^{-1} (\mathbf{z}_m(v_i^t) - \mathbf{c}_{i,m}^{t-1}), \quad (15)$$

Assume under the no-attack hypothesis, the squared Mahalanobis statistic $\mathcal{M}_{i,t}^{(\cdot)} \sim \chi_{k,\alpha}^2$, which is the $(1 - \alpha)$ -quantile of a chi-square distribution with k degrees of freedom. So flag the attack as

$$v_i^t \text{ as } \begin{cases} \text{Type 1 Attack(text)} & \text{if } \mathcal{M}_{i,t}^{(d)} > \chi_{k_d,\alpha}^2, \\ \text{Type 2 Attack(image)} & \text{if } \mathcal{M}_{i,t}^{(f)} > \chi_{k_f,\alpha}^2. \end{cases} \quad (16)$$

For the structural attacks, specifically object obstruction (Type 3) and object injection (Type 4), the detector relies on lightweight temporal heuristics rather than statistical distance. After each matching step, the algorithm keeps a two-frame sliding window of NodeSet activity. If an object that previously carried a high task-importance score ($\pi \geq \pi_{\text{high}}$) fails to obtain a match in both the current and the immediately preceding frame, the system labels the disappearance

an obstruction attack. Conversely, any NodeSet that first appears within the last two frames and whose reasonability score falls below a predefined threshold ($\rho \leq \rho_{\text{low}}$) is treated as an injection attack.

In the attack detection final step, if v_i^t is flagged as attack, it is appended to the $\mathcal{N}_{i,t}$ but excluded from future Gaussian updates; otherwise going to the Node Estimation process, including weight and resample, then stored in a clean reference $\tilde{\mathcal{N}}_{i,t}$.

3.3.3. Estimation.

After a new observation $v_{i,t}$ has been matched to object i and detected as a non-attack node, the particle filter estimates the new node by refining that observation by resampling historical detections that resemble it. The estimation proceeds as follows.

Let the newly matched observation of NodeSet i at frame t be $v_{i,t}$ and denote by

$$\tilde{\mathcal{N}}_{i,t-1} = \{v^{(1)}, \dots, v^{(M)}\} \subseteq \mathcal{N}_{i,t-1}, \quad M \geq 5,$$

the set of *non-attack* detections accumulated up to $t-1$. Considering each attribute as a particle, the filter updates $v_{i,t}$ by weighted resampling over this reference set.

For any scalar attribute $a \in \{p, \pi, \rho\}$ (probability, importance, reasonability), let $a^* = a(v_i^t)$ and $a^{(j)} = a(v^{(j)})$ ($j = 1 \dots M$). Define the weight

$$\sigma_a = \max(\text{Std}\{a^{(1:M)}\}, \sigma_{\min}), \quad (17)$$

$$w_j = \frac{\exp[-(a^{(j)} - a^*)^2 / (2\sigma_a^2)]}{\sum_{k=1}^M \exp[-(a^{(k)} - a^*)^2 / (2\sigma_a^2)]}. \quad (18)$$

So w_j is the normalized weight of the particle, based on its distance to the new particle. Similarly, for embedding at-

tributes, modality $m \in \{n, d, f\}$ (name, description, image) let $m^* = m(v_i^t)$ and $m^{(j)} = m(v^{(j)})$. Weight is defined as

$$sim_j = \frac{m^{(j)} \cdot m^*}{\|m^{(j)}\| \|m^*\|}, \quad w_j = \frac{\exp(\lambda_m sim_j)}{\sum_{k=1}^M \exp(\lambda_m sim_k)}, \quad (19)$$

with a scale factor $\lambda_m > 0$.

Then use the weight to resample M indices $s_1, \dots, s_M \sim \text{Multinomial}(w_{1:M})$ yields estimated scalar particle and embedding particle:

$$\hat{a} = \frac{1}{M} \sum_{k=1}^M a^{(s_k)}, \quad \hat{n} = \frac{\sum_{k=1}^M m^{(s_k)}}{\left\| \sum_{k=1}^M m^{(s_k)} \right\|}, \quad (20)$$

where $\hat{a}$ is the estimated new scalar particle.

Finally, replacing each raw attribute in v_i^t by its resampled estimate gives the estimated node

$$\hat{v}_{i,t} = (\hat{p}, \hat{\pi}, \hat{\rho}, \hat{n}, \hat{d}, \hat{f}), \quad (21)$$

which becomes the particle filter’s estimation state for object i at time t . If $M < 5$ (insufficient history), we skip resampling and simply set $\hat{v}_{i,t} = v_{i,t}$.

4. Experiment

In this section, we provide a detailed description of the *CADAR* experimental settings used for performance evaluation. We then present and analyze the numerical results of our experiments, demonstrating that *CADAR* significantly outperforms several baselines. An ablation study is also conducted to analyze the contributions of our key components.

4.1. Experimental Settings

CADAR-50K Dataset. The *CADAR*-50K dataset extends the AR-VIM dataset [25], which was designed to evaluate visual information manipulation in AR environments. *CADAR*-50K is the first publicly available dataset for AR cognitive-attack analysis, containing 375 videos across diverse scenes and more than 50K frames, covering all seven categories (Fig. 5 and Fig. 6). Each sample is an 8–12 second AR-captured video (recorded using a Meta Quest 3 or Samsung Galaxy S24), where virtual content is introduced at a specific frame to induce an attack. For the non-attack elements, we use irrelevant background objects, benign AR elements, and semantically benign prompts that can interfere with VLM outputs but do not alter the human-perceived task semantics.

Considering scene availability, the dataset was collected using two complementary methods: (1) a virtual-scene method, where fully synthetic environments are first generated and displayed on a monitor or VR headset, and AR content is then overlaid onto these virtual scenes before being captured through video recording. This enables rapid,

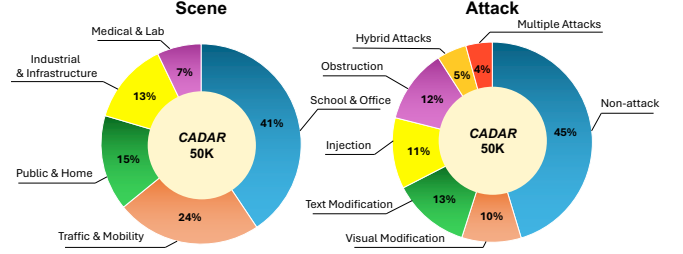


Figure 5. CADAR-50K dataset overview.

controllable creation of diverse attack scenarios; and (2) a real-world method, where AR headsets record first-person views in physical environments, introducing natural noise, lighting variation, and depth cues.

Task, Baselines and Metrics. We evaluate our model on the task of video-based cognitive attack classification. The *CADAR* dataset supports frame-wise detection, variable-length multi-label outputs, and localization of simultaneous attacks. We compare *CADAR* against two categories of baselines that similarly accept multiple reference frames as input and output attack classes: (1) multimodal VLMs, including state-of-the-art *OpenAI GPT-5*, *Google Gemini-2.5* [9] and *xAI Grok-4*, which perform fine-grained frame-level detection; and (2) supervised video models, the CNN-based *3D-ResNet* [23] and transformer-based *ViViT* [2], which output a single prediction per video.

In our first experiment (Table 1), we use class-specific accuracy and F1-score to assess overall detection performance. The class-specific accuracy is defined as $TP / (TP + FN + FP)$, which penalizes both missed detections and false alarms for that class while ignoring true negatives that dominate under severe class imbalance. For hybrid attack or multiple attack videos (Table 2 and 3), a prediction is considered correct only if all attack types are simultaneously identified. We also report per-class recall, $TP / (TP + FN)$, to measure correctness conditioned on the presence of the class.

4.2. Numerical Results and discussion

Cross-Scene Cognitive Attack Classification. The results in Table 1 demonstrate that *CADAR* achieves the highest overall accuracy (74.6%) and F1-score (84.2%) and its average accuracy exceeding the next best baseline models (*GPT-5-mini*) by 16%. *CADAR* attains the highest class-specific accuracy and F1 in 23 out of 25 attack-scene blocks. The margin is especially large for Visual and Obstruction attacks, where *CADAR* delivers strong gains, underscoring its robustness to fine-grained semantic distortions. We also observe that VLM baselines exhibit substantial accuracy fluctuations across different scenes, indicating that their reasoning processes are unstable and prone to hallucination. Because they rely on jointly processing all textual and visual inputs, they become increasingly sensitive

Table 1. Attack-wise Accuracy and F1-score (%) across scenes for frame-level and video-level baselines. Each attack type forms a block, with sub-rows indicating methods. Columns represent scene categories. CADAR outperforms VLM-based (GPT-5-mini, Gemini-2.5-flash) and supervised video models (3D-ResNet, ViViT) in 23 out of 25 attack-scene blocks.

Class-specific Accuracy / F1-score (%)								
Attack	Detection	Method	School&Office	Traffic&Mobility	Industrial&Infra	Medical&Lab	Public&Home	Avg Acc/F1
Text	Frame	CADAR (Ours)	68.8 / 80.2	69.0 / 78.2	78.5 / 91.1	71.0 / 82.4	72.7 / 80.1	72.0 / 82.4
		GPT-5-mini	50.6 / 67.2	59.6 / 74.7	52.1 / 68.5	52.5 / 68.9	61.1 / 75.9	55.2 / 71.0
		Gemini-2.5-flash	73.0 / 84.4	58.4 / 73.7	77.4 / 87.2	41.6 / 58.8	51.4 / 67.9	60.4 / 74.4
	Video	3D ResNet	12.5 / 22.2	10.9 / 19.6	12.8 / 22.6	15.6 / 27.0	40.0 / 57.1	18.4 / 29.7
		ViViT	26.3 / 41.7	70.6 / 82.8	25.0 / 42.1	33.3 / 50.0	43.5 / 60.6	39.7 / 55.4
Visual	Frame	CADAR (Ours)	80.3 / 92.1	79.2 / 85.2	67.2 / 78.9	69.7 / 81.0	70.4 / 84.5	73.4 / 84.3
		GPT-5-mini	51.0 / 67.6	61.5 / 76.2	50.6 / 67.2	45.5 / 62.5	59.8 / 74.9	53.7 / 69.7
		Gemini-2.5-flash	49.5 / 66.3	76.7 / 86.8	43.9 / 61.0	58.7 / 74.0	40.8 / 58.0	53.9 / 69.2
	Video	3D ResNet	16.5 / 28.3	7.2 / 13.3	8.3 / 15.3	12.7 / 22.5	8.3 / 15.4	10.6 / 19.0
		ViViT	22.2 / 36.4	44.4 / 61.5	20.0 / 33.3	28.6 / 44.4	25.0 / 40.0	28.0 / 43.1
Obstruction	Frame	CADAR (Ours)	78.2 / 87.3	85.1 / 91.9	81.2 / 89.3	78.3 / 89.1	80.7 / 92.1	80.7 / 89.9
		GPT-5-mini	75.4 / 85.9	46.0 / 63.0	61.7 / 76.3	46.3 / 63.3	63.2 / 77.4	58.5 / 73.2
		Gemini-2.5-flash	64.7 / 78.6	51.6 / 68.1	55.0 / 71.0	36.9 / 53.9	43.6 / 60.7	50.4 / 66.5
	Video	3D ResNet	8.1 / 15.0	3.0 / 5.9	5.0 / 9.5	9.4 / 17.2	4.5 / 8.7	6.0 / 11.3
		ViViT	50.0 / 66.7	54.5 / 70.6	46.2 / 63.2	71.4 / 83.3	41.7 / 42.3	52.8 / 65.2
Injection	Frame	CADAR (Ours)	76.9 / 81.1	81.4 / 89.5	72.2 / 78.9	73.5 / 79.0	74.0 / 82.6	75.6 / 82.2
		GPT-5-mini	69.1 / 81.7	60.7 / 75.6	56.3 / 72.0	55.2 / 71.2	63.3 / 77.5	60.9 / 75.6
		Gemini-2.5-flash	70.1 / 82.4	54.1 / 70.2	62.8 / 77.2	61.5 / 76.1	53.1 / 69.4	60.3 / 75.0
	Video	3D ResNet	6.6 / 12.3	12.8 / 22.7	9.8 / 17.8	13.3 / 23.4	15.7 / 27.2	11.6 / 20.7
		ViViT	30.0 / 46.2	45.5 / 62.5	20.0 / 33.3	25.0 / 40.0	55.6 / 71.4	35.2 / 50.7
Non attack	Frame	CADAR (Ours)	75.3 / 80.8	68.9 / 80.2	71.6 / 84.9	74.6 / 85.2	67.2 / 79.4	71.5 / 82.1
		GPT-5-mini	71.8 / 83.6	52.1 / 68.5	62.8 / 77.1	70.5 / 82.7	68.1 / 81.0	65.1 / 77.4
		Gemini-2.5-flash	54.2 / 70.3	38.2 / 55.3	44.0 / 61.1	41.1 / 58.3	44.1 / 61.2	44.3 / 61.2
	Video	3D ResNet	8.5 / 15.7	11.7 / 20.9	8.6 / 15.9	15.9 / 27.5	29.4 / 45.5	14.8 / 25.1
		ViViT	40.0 / 57.1	15.4 / 26.7	7.7 / 14.3	40.0 / 57.1	30.8 / 47.1	26.8 / 40.5
Overall Mean (per method): CADAR: 74.6 / 84.2 GPT-5-mini: 58.7 / 73.4 Gemini-2.5-flash: 53.9 / 69.3 3D ResNet: 12.3 / 21.1 ViViT: 36.5 / 51.0								

Table 2. Recall comparison for hybrid-attack scenarios (%), CADAR achieves the highest recall across both hybrid combinations.

Hybrid Attack Type	Recall of Method (%)			
	GPT-5-mini	Grok-4-fast	CADAR	Gemini-2.5-flash
Text+Visual	35.0	41.2	76.4	29.9
Obstruction+Injection	32.7	26.1	80.4	45.8

Table 3. Recall (%) of attack detection under different numbers of simultaneous attacks. CADAR maintains strong performance as the number of attacks increases, whereas baseline models degrade substantially.

Method	Number of Attacks				Avg
	1 Attack	2 Attacks	3 Attacks	4 Attacks	
GPT5-mini	66.4	40.2	31.5	29.6	41.9
Grok-4-fast	69.7	55.0	51.3	36.5	53.1
Gemini-2.5-flash	61.7	43.6	33.0	31.5	42.5
CADAR	81.0	78.3	75.2	67.2	75.4

to misleading cues, malicious prompts, and complex visual environments. This vulnerability highlights the advantage of our neuro-symbolic approach, which offers more controlled and explainable reasoning under diverse AR scenarios.

On the other hand, traditional video-classification models (3D-ResNet and ViViT) perform poorly across all attack types, suggesting that the models are inadequate for capturing the fine-grained semantic inconsistencies central to cognitive attack detection. Their limited performance is further exacerbated by the lack of large-scale, AR-specific train-

ing data, making these models particularly weak in zero- or few-shot scenarios.

Overall, the results indicate that *CADAR*’s neurosymbolic design and temporal reasoning components provide strong advantages for detecting subtle, localized, and multi-instance AR cognitive attacks, achieving robust performance across diverse environments and attack conditions.

Hybrid and Multiple Attacks Table 2 and 3 evaluate model robustness in hybrid and multi-attack settings. In hybrid-attack scenarios, *CADAR* attains the highest recall for both Text+Visual(76.4%) and Obstruction+Injection(80.4%) cases and surpasses all VLM baselines by a substantial margin. This demonstrates that the proposed neurosymbolic graph reasoning framework can effectively detect the attacks separately. In multiple attack scenarios, the performance of VLM baselines declines sharply as attack complexity grows, whereas *CADAR* retains strong recall, from 81.0% for a single attack to 67.2% for four simultaneous attacks, showing the smallest performance drop among all compared methods. These results highlight *CADAR*’s resilience in multi-attack scenarios and its clear advantage in detecting objects in parallel.

Effect of Scene Complexity. The recall trends in Fig. 7(a) reveal a clear divergence between VLM-based baselines and *CADAR* as scene complexity increases. For GPT-5-mini and Gemini-2.5-flash, recall drops sharply when the number of key objects and frames increases, suggesting that conven-

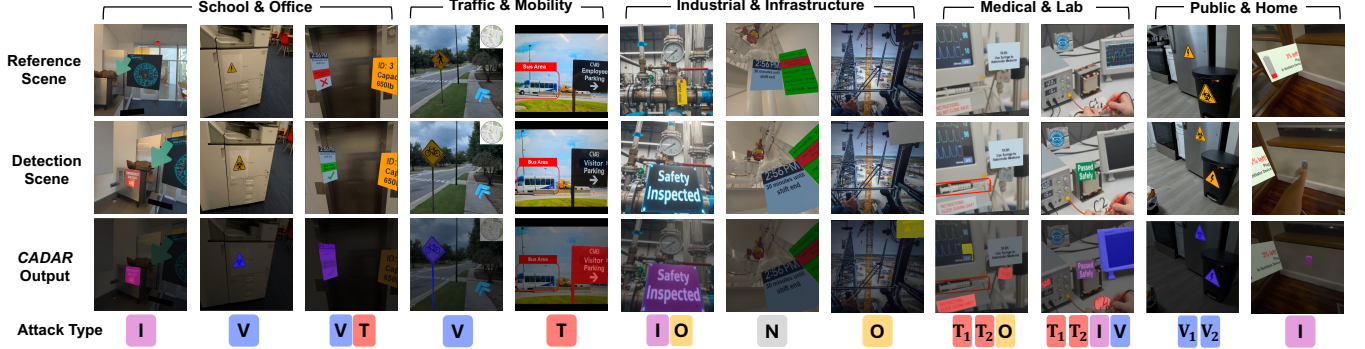


Figure 6. Visualization frame examples of *CADAR* outputs across five scene categories in *CADAR*-50K 375 videos. Rows show the Reference Scene, Detection Scene, and *CADAR* Output. Output attack types: I = Injection, V = Visual, T = Text, O = Obstruction, N = Non-attack. Some examples contain hybrid or multiple attacks.

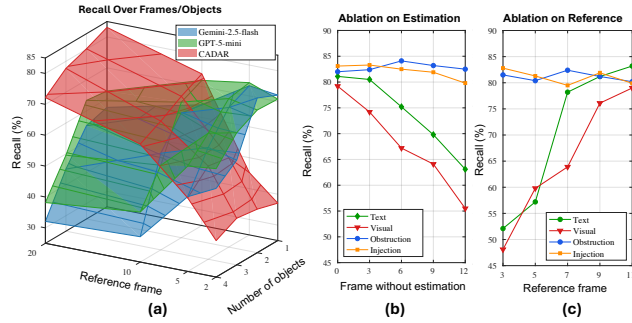


Figure 7. Recall under increasing reference frames and object quantities (a), and ablation studies on the estimation module (b) and the number of reference frames (c).

tional VLMs struggle with reasoning over long visual and textual context and are easily affected by irrelevant or distracting content. In contrast, *CADAR* performance remains stable as reference frames increase, since it extracts complex scene information into a structural spatial-temporal perception graph. *CADAR* improves its decision accuracy by accumulating prior evidence through additional reference frames, and evaluates objects and attacks separately rather than relying on a single holistic reasoning step. The *CADAR* design results in substantially smaller performance degradation compared with standard VLMs.

4.3. Ablation Study

Estimation Module. Fig. 7(b) shows our ablation study examining the impact of the estimation module in particle filtering. When a polluted node that might have bad data due to VLM unstable output or due to an undetected attack, the estimation module’s weighting and resampling can effectively prevent it from corrupting the ground truth knowledge. We randomly sample 6 videos per base attack type (24 in total) from the test split for the ablation study. As shown in the left plot of the figure, for text and visual modification attacks, the recall drops significantly as the number of frames without the estimation module increases. Specif-

ically, the recall for text attacks decreases from approximately 81% to 63% and from approximately 79% to 55% for visual attacks. This indicates that the estimation module is crucial for correctly identifying and mitigating errors in more subtle attack types. In contrast, for obstruction and injection attacks, the recall remains relatively stable, suggesting these attacks are more straightforward to detect and less dependent on the estimation module’s corrective capabilities.

Reference Frames. Fig. 7(c) shows the impact of the number of reference frames on recall. A larger number of reference frames, or more prior knowledge of the scene, will result in higher recall. For text and visual modification attacks, increasing the number of reference frames from 3 to 11 significantly improves performance. The recall for text attacks increases from around 52% to 83% and from around 48% to 79% for visual attacks. This demonstrates that a larger set of reference frames provides more prior knowledge for more accurate statistical reasoning, which is essential for detecting subtle text and visual changes. Similar to the estimation module study, the recall for obstruction and injection attacks remains largely unaffected by the number of reference frames, consistently staying around 80%. This reinforces the finding that these attacks are less sensitive to the amount of contextual information and prior knowledge.

5. Conclusion

We presented *CADAR*, a neuro-symbolic framework that couples a perception graph with particle-filter reasoning to yield interpretable attack detection in AR/MR. On the *CADAR*-50K dataset, *CADAR* performs strongly across all attack types, and ablations highlight the value of our estimation module and richer reference histories. Overall, *CADAR* highlights the value of neuro-symbolic design by combining the adaptability of foundation models with symbolic reasoning for a robust and interpretable AR safety mechanism.

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