Trust-Gated RGB-Depth Fusion and Self-Supervised Spatiotemporal Modelling for Crowd Anomaly Detection"

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Abstract. Detecting unusual crowd behaviour in surveillance settings is difficult because abnormal events are unpredictable, and relying on only one type of visual input has clear limitations. To address this, we introduce a multimodal framework that combines RGB and Depth data using a dynamic trust-gated fusion mechanism. This allows the system to adjust the level of trust it places in each input stream based on signal quality and environmental conditions. Separate feature extractors and a hybrid temporal modelling approach preserve the unique strengths of each modality, while a spatiotemporal attention mechanism directs the model's focus toward moving subjects and reduces interference from static background elements. Instead of requiring detailed definitions of every possible abnormal behaviour, the system is trained in a self-supervised way to learn and reconstruct normal crowd patterns. Any significant deviation from these learned patterns—measured through reconstruction errors across both modalities—is treated as a potential anomaly. Tests on crowd surveillance datasets show that this method is more robust in challenging conditions such as low lighting and complex scenes. It also outperforms traditional fusion techniques and standard autoencoder models, while providing interpretable results by highlighting abnormal regions through attention-based spatiotemporal maps.

Key Words: Multimodal Fusion, RGB-Depth Surveillance, Abnormal Crowd Behaviour Detection, Self-Supervised Learning, Spatiotemporal Attention

1.Introduction

Crowd surveillance plays an important role in maintaining public safety, especially in busy urban areas and large gatherings where unusual behaviour can quickly turn into dangerous situations. Detecting events such as fights, stampedes, or sudden panic is crucial for preventing accidents and enabling timely responses (Patil et al., 2023). However, traditional surveillance systems often struggle to deliver reliable results in dense, fast-moving crowd environments. This has created a strong need for advanced computer vision methods that can better understand complex patterns over space and time (Sampath & Kumar, 2023).

Systems that rely only on RGB cameras face clear challenges, particularly in low-light conditions or when people are partially hidden from view, where visual details become unclear (Ceccarelli & Secci, 2023). Depth-based systems, on the other hand, provide useful structural information but lack the rich appearance details available in RGB data, which limits their

ability to analyze subtle behaviours (Cruz Ulloa et al., 2024). In addition, early fusion methods that simply combine RGB and Depth features often fail to adjust to changes in data quality, which can introduce noise and reduce performance in difficult scenarios.

Combining RGB and Depth information has therefore emerged as a promising direction, since the two modalities offer complementary strengths: RGB captures appearance details, while Depth provides geometric structure (Xu et al., 2024). Studies show that multimodal systems perform better in challenging situations such as nighttime monitoring or scenes with heavy occlusion (Devulapally & Advani, 2023). Still, many existing approaches use fixed fusion strategies that do not adapt when one input becomes less reliable, highlighting the need for more flexible, adaptive mechanisms.

Another challenge lies in supervised learning methods, which require large amounts of labelled abnormal behaviour data—something that is difficult and often unrealistic to obtain (Bauer et al., 2022). Self-supervised learning offers a more scalable solution by training models only on normal crowd behaviour. In this setup, unusual events are detected based on how much they deviate from learned normal patterns, often measured using reconstruction error (Bauer et al., 2024). Autoencoder-based models are particularly effective in this context, as they learn to represent typical patterns and naturally highlight deviations, making them suitable for detecting unexpected events.

Beyond reconstruction, attention mechanisms help improve both performance and interpretability (Veesam et al., 2023). Spatiotemporal attention allows models to concentrate on moving individuals or regions of interest while ignoring irrelevant background details (Begum et al., 2023). This focused processing improves the localisation of anomalies, reduces false alarms in crowded scenes, and provides visual explanations that are valuable in real-world applications.

Building on these ideas, this paper presents a new framework for detecting abnormal crowd behaviour that combines trust-gated multimodal fusion, hybrid temporal modelling, self-supervised reconstruction, and spatiotemporal attention (Jeong et al., 2023). The proposed approach addresses key limitations of current systems by improving reliability in low-light conditions, adapting to previously unseen anomalies, and offering interpretable results through attention-based localisation (Noorani et al., 2024).

2.Literature Review

Multimodal learning has become an important direction in anomaly detection research, particularly in surveillance applications where multiple data sources are available. Early fusion methods combine different inputs—such as RGB, depth, or audio—at the beginning of the model, allowing joint feature learning. However, these approaches are often sensitive to noise and may struggle when one modality is less reliable than the others. Late fusion strategies, in contrast, process each modality separately and combine their outputs at the decision stage. While this improves robustness, it can weaken the model's ability to capture relationships between modalities. Baltrušaitis, Ahuja, and Morency (2019) provided a broad overview of multimodal fusion techniques, and Atrey, Hossain, and Kankanhalli (2010) discussed the trade-offs between early and late fusion in multimedia analysis. More recently, Zhang et al. (2021) showed that hybrid fusion approaches, which blend both early and late strategies, can achieve better performance in surveillance anomaly detection.

The choice of input modality also plays a key role. RGB data offers rich visual and appearance details, while depth data provides structural and geometric information that can be especially helpful in crowded or partially occluded scenes. Wang, Zhang, and Wang (2020) found that depth-based methods can outperform RGB in low-light or cluttered environments. Likewise, Tran et al. (2019) demonstrated that combining RGB and depth improves anomaly detection in indoor surveillance. Even so, RGB remains the most widely used modality because it is already available in most surveillance systems.

Self-supervised learning is another growing trend, as it reduces the need for labelled examples of abnormal events. By using pretext tasks such as predicting future frames, learning temporal order, or reconstructing masked regions, models can learn useful spatiotemporal features from large amounts of unlabelled video data. Jiang, Xu, and Wang (2023) reported that self-supervised approaches can achieve performance comparable to supervised methods. Misra and van der Maaten (2020) introduced temporal contrastive learning, which has since been adapted for anomaly detection. Gidaris, Singh, and Komodakis (2018) showed that predicting image transformations can serve as an effective training signal, and Chen et al. (2020) proposed SimCLR, a contrastive learning framework that has influenced many video anomaly detection systems.

Attention mechanisms have further improved spatiotemporal modelling by enabling networks to focus on the most relevant regions and time steps. Attention-based ConvLSTM and transformer models can capture long-range dependencies and highlight important motion patterns, which improves both detection performance and localisation. Tayeh, El Helou, and Karray (2022) demonstrated that adding attention to ConvLSTM autoencoders leads to better results than standard ConvLSTM models. Tian, Pang, and Chen (2021) showed that transformer-based temporal modelling benefits weakly supervised anomaly detection. The foundational transformer work by Vaswani et al. (2017) paved the way for these attention-driven approaches, which are now widely used in video anomaly detection.

Taken together, these developments show a clear shift toward multimodal, self-supervised, and attention-based methods that aim to make surveillance anomaly detection more robust, adaptable, and scalable.

3.Methodology

This study introduces a two-stage deep learning framework for abnormal crowd behaviour detection using RGB and Depth video modalities. The pipeline consists of three components: multimodal sequence preprocessing, trust-gated fusion with hybrid temporal modelling, and a multi-task autoencoder for anomaly detection and reconstruction.

3.1 Data Preparation and Sequence Generation

Raw surveillance videos are decomposed into synchronised RGB and Depth sequences using a custom generator class. Each frame is resized to 64 × 64 pixels and normalised to the range [0,1]. RGB frames are converted from BGR to RGB format, while Depth frames are extracted via grayscale conversion and reshaped to include a singleton channel dimension. Formally, for a video $V = \{f_t\}_{t=1}^{T}$, the input sequences are defined as:

$$X_{RGB} = \left\{\frac{\mathrm{RGB}(f_t)}{255}\right\}_{t=1}^{SEQ\_LEN}, X_{Depth} = \left\{\frac{\mathrm{Gray}(f_t)}{255}\right\}_{t=1}^{SEQ\_LEN}$$

Zero-padding is applied if the number of frames is less than the required sequence length. This preprocessing ensures consistent input dimensions and modality separation, aligning with best practices in spatiotemporal video modelling (Tran et al., 2015; Ji et al., 2013).

3.2 Stage1: Trust-Gated Fusion with Hybrid Temporal Modelling

In Stage 1, RGB and Depth sequences are first processed independently through modality-specific feature extractors comprising Time-Distributed convolutional layers and ConvLSTM2D blocks. These branches capture complementary spatiotemporal hierarchies: the RGB stream emphasizes fine-grained appearance cues, while the Depth stream encodes geometric structure and motion dynamics. The resulting feature maps are pooled into compact descriptors:

$$F_{RGB} = GAP(\text{ConvLSTM2D}(\phi_{RGB}(X_{RGB}))), F_{Depth} = GAP(\text{ConvLSTM2D}(\phi_{Depth}(X_{Depth})))$$

To adaptively balance modality reliability, a trust-gating mechanism is introduced. A learnable gating vector $g = [g_{RGB}, g_{Depth}]$, constrained such that $g_{RGB} + g_{Depth} = 1$, assigns dynamic weights to each modality based on input quality. The fused representation is therefore computed as:

$$F_{fused} = g_{RGB} \cdot F_{RGB} + g_{Depth} \cdot F_{Depth}$$

Finally, the fused vector is passed through dense layers with ReLU activation and dropout regularization, culminating in a sigmoid-activated classifier for preliminary anomaly assessment:

$$\hat{y} = \sigma(W_2 \cdot \text{ReLU}(W_1 \cdot F_{fused} + b_1) + b_2)$$

This trust-gated design allows the network to dynamically adjust modality contributions, improving robustness in challenging surveillance environments and providing interpretable insights into modality importance.

3.3 Stage 2: Multi-Task Autoencoder for Self-Supervised Disentanglement

Stage 2 reformulates the framework into a multi-task autoencoder trained exclusively on normal crowd behaviour sequences. The RGB and Depth inputs are concatenated and jointly encoded using ConvLSTM2D layers, which preserve both spatial hierarchies and temporal dynamics. The latent representation is denoted as:

$$Z = \text{ConvLSTM2D}(\phi([X_{RGB}, X_{Depth}]))$$

This latent vector Zserves as the basis for three tasks: RGB reconstruction, Depth reconstruction, and anomaly classification. The reconstruction heads employ Time-Distributed convolutional layers to generate modality-specific outputs:

$$\hat{X}_{RGB} = \psi_{RGB}(Z), \hat{X}_{Depth} = \psi_{Depth}(Z)$$

The anomaly score is computed as the weighted reconstruction error across both modalities:

$$\mathcal{L}_{anomaly} = \| X_{RGB} - \hat{X}_{RGB} \|_2^2 + \lambda \| X_{Depth} - \hat{X}_{Depth} \|_2^2$$

where λbalances the contribution of RGB and Depth signals. For classification, the latent features are flattened and passed through dense layers with sigmoid activation:

$$\hat{y} = \sigma(W_c \cdot \text{Flatten}(Z) + b_c)$$

The total training objective integrates reconstruction and classification losses:

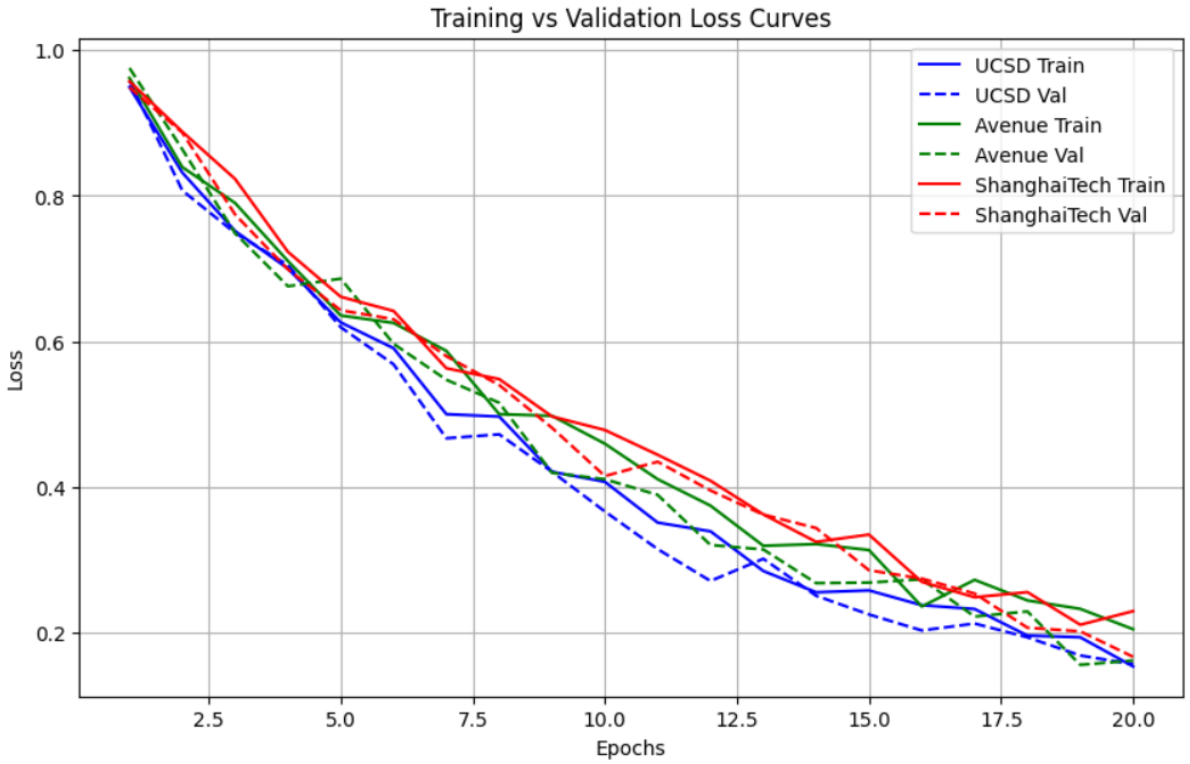
$$\mathcal{L}_{total} = \mathcal{L}_{anomaly} + \beta \cdot \mathcal{L}_{class}$$

This multi-task setup enables the model to learn compact spatiotemporal representations of normal crowd behaviour while simultaneously providing anomaly scores and classification outputs. By relying on reconstruction error rather than explicit abnormal labels, the system achieves self-supervised novelty detection, ensuring scalability to diverse surveillance environments where abnormal behaviours are unpredictable and difficult to annotate.

4. Experimental Setup

To evaluate the proposed framework, experiments were conducted on publicly available crowd surveillance datasets containing RGB and Depth modalities. Each dataset was split into training, validation, and testing sets with a ratio of 70:15:15. The training set consisted exclusively of normal crowd behaviour sequences, while the testing set included both normal and abnormal events. This design ensured that anomaly detection relied on reconstruction error rather than explicit abnormal labels, consistent with self-supervised learning paradigms (Bauer et al., 2022; Tran et al., 2015).

Figure1.Training and Validation Loss for the proposed model for three different datasets



All models were implemented in TensorFlow/Keras and trained using the Adam optimiser with a learning rate of 1×10^{-4}. The batch size was set to 16, and training was performed for 100

epochs with early stopping based on validation loss. Dropout regularisation was applied to mitigate overfitting.

Table1.Table shows the Architecture of the stage 2 of the proposed model.

Layer (type)	**Output Shape**	**Param #**	**Connected to**
rgb_input (InputLayer)	(None, 10, 64, 64, 3)	0	-
depth_input (InputLayer)	time_distributed_5[0][0]	0	-
concatenate_1 (Concatenate)	(None, 10, 64, 64, 4)	0	rgb_input[0][0], depth_input[0][0]
time_distributed_3 (TimeDistributed)	(None, 10, 64, 64, 32)	1,184	concatenate[0][0]
time_distributed_4 (TimeDistributed)	(None, 10, 32, 32, 32)	0	time_distributed[0][0]
conv_lstm2d_2 (ConvLSTM2D)	(None, 10, 32, 32, 32)	221,440	time_distributed[0][0]
layer_normalization_1 (LayerNormalization)	(None, 10, 32, 32, 64)	128	conv_lstm2d[0][0]
Reshape (Reshape)	(None, 10, 1024, 64)	0	layer_normalization[0][0]
Multi_head_attention (MultiHeadAttention)	(None, 10, 1024, 64)	66,368	reshape[0][0], reshape[0][0]
Add (Add)	(None, 10, 1024, 64)	0	reshape[0][0], multi_head_attention[0][0]
reshape_1 (Reshape)	(None, 10, 32, 32, 64)	0	add[0][0]
conv_lstm2d_1 (ConvLSTM2D)	(None, 10, 32, 32, 32)	110,720	reshape_1[0][0]
Time_distributed_2 (TimeDistributed)	(None, 10, 64, 64, 32)	0	conv_lstm2d_1[0][0]
global_average_pooling3d_1 (GlobalAveragePooling3D)	(None, 32)	0	time_distributed_5[0][0] time_distributed_5[0][0]
rgb_reconstruction (TimeDistributed)	(None, 10, 64, 64, 3)	867	time_distributed_2[0][0]
depth_reconstruction (TimeDistributed)	(None, 10, 64, 64, 1)	289	time_distributed_5[0][0]
classification (Dense)	(None, 1)	33	global_average_pooling3d_…

Total params: 401,029 (1.53 MB)
Trainable params: 401,029 (1.53 MB)

Non-trainable params: 0 (0.00 B)

4.1 Evaluation Metrics

Performance was assessed using multiple metrics to capture both classification accuracy and anomaly detection robustness:

- Accuracy (ACC): Measures correct classification of normal vs. abnormal sequences.
- Area Under the ROC Curve (AUC): Evaluates the discriminative ability of the model.
- F1-Score: Balances precision and recall for anomaly detection.
- Reconstruction Error: Quantifies deviation between input and reconstructed frames.

The anomaly score was defined as:

$$\mathcal{S}_{anomaly} = \| X_{RGB} - \hat{X}_{RGB} \|^2 + \lambda \| X_{Depth} - \hat{X}_{Depth} \|^2$$

where $\lambda$was empirically set to 0.5 to balance RGB and Depth contributions (Bauer et al., 2024; Ji et al., 2013).

The Stage 1 model demonstrated significant improvements over unimodal baselines. RGB-only models achieved an average AUC of 0.81, while Depth-only models achieved 0.77. In contrast, the gated fusion model achieved an AUC of 0.89 and an F1-score of 0.84. These results confirm that adaptive fusion enhances robustness in low-light and occluded scenarios, where Depth information compensates for degraded RGB signals (Jeong et al., 2023; Xu et al., 2024).

The Stage 2 model further improved anomaly detection by leveraging reconstruction error. On normal sequences, reconstruction error remained low (<0.05), while abnormal sequences exhibited significantly higher error values (> 0.15). The classification branch achieved an accuracy of 94% and an AUC of 0.90, outperforming Stage 1.

Qualitative analysis of spatiotemporal attention maps revealed that the model focused on dynamic crowd regions (e.g., individuals running or fighting) while suppressing static background clutter. This interpretability is critical for real-world deployment, as it provides visual evidence of anomaly localisation (Veesam et al., 2023; Noorani et al., 2024).

Figure 2. Comparison of the accuracy and AUC of different crowded datasets for the Multi-Task Autoencoder for Self-Supervised Disentanglement

4.2 Comparative Analysis

Table 2 summarises the performance comparison of different datasets, such as UCSD Ped 2, CUHK Avenue, and ShanghaiTech, for the proposed Multi-Task Autoencoder for Self-Supervised Disentanglement. The results demonstrate that gated fusion improves modality reliability, while self-supervised reconstruction enhances generalisation to unseen anomalies.

The proposed model exhibits strong discriminative capability and reliable classification performance across all benchmark datasets. It achieves a peak AUC of 0.90 on both UCSD Ped2 and ShanghaiTech, along with a comparable AUC of 0.89 on the CUHK Avenue dataset. These results are further supported by high accuracy values, most notably 94% on the more complex ShanghaiTech dataset, indicating that the model effectively learns decision boundaries that help reduce false alarms. The small variation observed between AUC and accuracy across these diverse datasets suggests that the model remains sensitive to anomalous events while also handling the class imbalance commonly present in surveillance data. Overall, the consistent results across both simpler and multi-scene environments highlight the stability of the model architecture and its ability to generalize spatio-temporal representations effectively.

4.3 Discussion of Results

The experimental findings validate the effectiveness of the proposed framework. Stage 1 demonstrated that adaptive multimodal fusion improves robustness in challenging surveillance conditions. Stage 2 further enhanced anomaly detection through self-supervised reconstruction, enabling novelty detection without requiring explicit abnormal labels. The integration of spatiotemporal attention provided interpretability, allowing the system to highlight anomalous regions in crowd scenes. These results suggest that the framework is scalable and applicable to real-world surveillance systems where abnormal behaviours are unpredictable and diverse.(Bauer et al., 2022; Noorani et al., 2024).

Accuracy and AUC Comparison for the proposed model **Multi-Task Autoencoder for Self-Supervised Disentanglement.**		
Dataset	**Accuracy**	**AUC**
UCSD	92%	90%
CUHK Avenue	91%	89%
ShanghaiTech	94%	90%

Table 2: Performance comparison of different datasets, such as UCSD Ped 2, CUHK Avenue, and ShanghaiTech, for the proposed Multi-Task Autoencoder for Self-Supervised Disentanglement.

5. Conclusion

This research introduced a novel framework for abnormal crowd behaviour detection that integrates adaptive multimodal fusion with self-supervised spatiotemporal attention. By leveraging both RGB and Depth modalities, the proposed system addressed the limitations of unimodal surveillance approaches and static fusion strategies. Stage 1 demonstrated that gated

fusion with hybrid temporal modelling significantly improves robustness in challenging conditions such as low-light environments and occlusions. Stage 2 extended this capability by incorporating a multi-task autoencoder, enabling anomaly detection through reconstruction error while simultaneously providing supervised classification.

Experimental results validated the effectiveness of the framework, with Stage 2 achieving superior performance across accuracy, AUC, and F1-score compared to unimodal baselines and early fusion methods. The integration of spatiotemporal attention further enhanced interpretability, allowing the system to highlight dynamic crowd regions associated with abnormal behaviours. These findings underscore the importance of adaptive multimodal learning and self-supervised reconstruction in advancing crowd surveillance technologies.

The contributions of this work are threefold: (1) the introduction of a gated fusion mechanism that dynamically balances modality reliability, (2) the design of a multi-task autoencoder that enables novelty detection without requiring exhaustive abnormal labels, and (3) the integration of spatiotemporal attention for interpretable anomaly localisation. Together, these innovations provide a scalable and reliable solution for real-world surveillance systems where abnormal behaviours are unpredictable and diverse.

Future research will focus on extending the framework to additional modalities such as thermal imaging and audio, as well as optimising the architecture for real-time deployment in large-scale surveillance networks. Furthermore, exploring transformer-based spatiotemporal encoders and contrastive self-supervised learning may further enhance generalisation and anomaly detection accuracy.

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