SAVCHOI: Detecting Suspicious Activities using Dense Video Captioning with Human Object Interactions

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Abstract

Detecting suspicious activities in surveillance videos is a longstanding problem in real-time surveillance that leads to difficulties in detecting crimes. Hence, we propose a novel approach for detecting and summarizing suspicious activities in surveillance videos. We have also created ground truth summaries for the UCF-Crime video dataset. We modify a pre-existing approach for this task by leveraging the Human-Object Interaction (HOI) model for the Visual features in the Bi-Modal Transformer. Further, we validate our approach against the existing state-of-the-art algorithms for the Dense Video Captioning task for the ActivityNet Captions dataset. We observe that this formulation for Dense Captioning performs significantly better than other discussed BMT-based approaches for BLEU@1, BLEU@2, BLEU@3, BLEU@4, and METEOR. We further perform a comparative analysis of the dataset and the model to report the findings based on different NMS thresholds (searched using Genetic Algorithms). Here, our formulation outperforms all the models for BLEU@1, BLEU@2, BLEU@3, and most models for BLEU@4 and METEOR falling short of only ADV-INF Global by 25% and 0.5%, respectively.

1. Introduction

We are interested in the problem of detecting suspicious (or criminal) activities from a real-time surveillance feed. For this purpose, several approaches have been discussed [23, 24], but not many formulations can detect criminal activities in surveillance feeds. Today, there are CCTV cameras at every corner, commercial outlet, and school. Hence, it’s challenging to process and analyze this large amount of surveillance feed by humans. Monitoring this data remains a challenging problem due to issues like restricted access to surveillance data because of privacy concerns and poor quality of surveillance footage.

This research presents a novel approach for detecting suspicious and criminal behavior in videos by leveraging and combining the architecture of two different algorithms that are state-of-the-art in detecting Human-Object Interactions and Dense Video Captioning. This paper discusses the problem formulation as a combination of dense summary generation (using a two-way disentanglement approach) in the videos and then classifying the generated summaries. Hence, the architecture uses a sequential combination of a Human-Object Interaction pipeline and selective Bi-Modal Dense Video Captioning (for Audio inputs). This paper leverages the downstream task of text classification to emphasize the capability of the summary generated. For this, the classifier was trained exhaustively on crime-based data to classify the captions as suspicious or not (criminal and non-criminal). This architecture allows us to transfer the task of crime detection using video (for which the data is not freely accessible) to crime detection using text (an easily accessible modality). Figure 1 presents a working example of the proposed method. This sequence of images is from a video of the ‘Arrest’ category in the UCF-Crime dataset. Figure 2 depicts the data flow diagram for our approach.

This work proposes a five-fold contribution to the pre-
existing literature for dense captioning and surveillance-based detection.

1. Introduced a novel modified architecture for detecting anomalous and suspicious behaviors in videos.

2. Augment ground-truth summaries to the UCF-crime video dataset \[38\] for training the modified models.

3. Curate a dataset for the text-based description of suspicious and non-suspicious activities using the CHA-RADES dataset \[35\] and the DPS report dataset\[^1\]\ (which was scraped using BeautifulSoup).

4. Presented optimization setting of a hyperparameter (here, NMS threshold value) of the model to improve the BLEU@1 of the generated summaries.

5. Perform comparative analysis on proposed model architectures and evaluate them on the ActivityNet Captions dataset.

The remainder of this research work is structured as follows. Section 2 discusses a literature survey on the problem and architecture. Section 3 discusses the datasets used and Section 4 expands on the proposed architecture. The results are discussed in Section 5 and further analyzed and compared in Section 6. We discuss some Dataset Limitations and Ethical Considerations in\[^2\] and \[^3\] respectively. Finally, we conclude this research in Section 9 with a possibility for future extensions to this work. The final section then discusses the ethical considerations entailed in this research.

\[^1\]https://dps.usc.edu/category/alerts/

\[^2\]The remainder of this research work is structured as follows. Section 2 discusses a literature survey on the problem and architecture. Section 3 discusses the datasets used and Section 4 expands on the proposed architecture. The results are discussed in Section 5 and further analyzed and compared in Section 6. We discuss some Dataset Limitations and Ethical Considerations in\[^2\] and \[^3\] respectively. Finally, we conclude this research in Section 9 with a possibility for future extensions to this work. The final section then discusses the ethical considerations entailed in this research.
for Human Object Interaction Detection)—based on a SWIN-transformer [23] as its backbone ensures that its detections are spatially coherent. Meanwhile, the querying mechanism ensures that only the interaction with the highest confidence score gets chosen between different Human and Object interactions. A more recent approach to action recognition deals with the usage of Timesformer [2], where self-attention is applied temporally and spatially within each patch on datasets like Kinetics-600 [6].

2.2. Surveillance-based Crime Detection

Currently, human activity detection in surveillance videos relates closely to formulating the problem of anomaly detection as a binary classification task [33, 32, 38]. In this domain, Action Recognition and Detection have become vital for detecting criminal activities like robbery, shooting, fighting, etc. Moreover, a substantial amount of research postulates this problem of Surveillance-based Crime Detection as a multi-task problem with multiple modalities [40, 25, 24]. It suggests that advancement in deep learning is one of the primary motivations for advancing Human Activity Recognition in video surveillance data. Feature extraction [38, 43, 24, 41] has played a vital role in detecting and recognizing Spatio-temporal features using 3D Convolutions [39, 7]. Recently, two different techniques—namely, Attention mechanisms [43, 24, 40] and Graph Representation Learning [46, 4]—have been used in surveillance videos for detecting various features and have been one of the motivations for choosing an attention-based mechanism in this contribution. Despite leveraging various techniques, the application of crime-based video detection remains a challenge to be solved efficiently. It is primarily due to the technical and other challenges discussed in the next sub-section.

2.3. Dense Video Captioning

This task was first defined by [22], and it later integrated context awareness using Bidirectional Single-Stream Temporal (SST) Action Proposals in [3] and Self-Critical Sequence Training using Actor-Critic Method with different metrics (CIDEr and METEOR [30]). In 2019, [27, 17, 16] implemented coherent captioning using the SST module and Pointer Networks. With the advent of transformer architectures, there has been an increase in end-to-end architectures for dense captioning [29, 16, 17]. But, the task of creating video-descriptive summaries for real-time surveillance is yet to be solved effectively. In these applications, the earlier hypotheses got limited by the data availability. The text-descriptive capability of models provides visual-semantic feature representation from video in natural language. This perspective suggests the usage of exhaustive descriptions of videos by partially (or completely) determining the actions (here, in a surveillance video) that need to be summarized. It had been studied in more detail by [13], which led to leveraging natural language descriptions while recognizing actions in a zero-shot setting for the UCF-101 [37]. Later, [11] proposed a method for understanding the video streams and storing them as text (to save on storage space) using natural language generation. We have used convolutions and bi-directional recurrent layers for the same. This approach used action recognition, object recognition, and human-specific datasets like UET Video Surveillance, AGRITRUSION, and TRECViD [21].

3. Datasets

Different datasets used for training different modules of the architecture—Human Object Interaction module, Dense Video Captioning module, and Text Classification task, are discussed in this section. Further, we also present our own two data-based contributions.

1. A dataset for ground truth captions of UCF crimes [38] data (described in section 3.2).

2. A dataset for a text-based description of suspicious and non-suspicious activities (described in section 3.3).
Table 1. A brief Comparison of detection made by CDN, QAHOI, and fine-tuned DE-TR models.

| Model        | Full(D) | Rare(D) | Non-Rare(D) | Full(KO) | Rare(KO) | Non-Rare(KO) |
|--------------|---------|---------|-------------|----------|----------|--------------|
| UPT-base     | 32.04   | 29.21   | 33.71       | 34.89    | 29.81    | 36.49        |
| CDN-S (R50)  | 31.44   | 27.39   | 32.64       | 34.09    | 29.63    | 35.42        |
| CDN-B (R50)  | 31.78   | 27.55   | 33.055      | 34.53    | 27.93    | 35.96        |
| CDN-L (R50)  | 32.07   | 27.19   | 33.53       | 34.79    | 29.48    | 36.38        |
| QAHOI-Tiny   | 28.41   | 22.47   | 30.27       | 30.99    | 24.83    | 32.84        |
| QAHOI-Base+  | 33.58   | 25.86   | 35.88       | 35.34    | 27.24    | 37.76        |
| QAHOI-Large+ | 35.78   | 29.80   | 37.56       | 37.59    | 31.36    | 39.36        |
| DE-TR (fine-tuned) | 31.56   | 28.41   | 29.23       | 35.41    | 30.71    | 37.52        |

3.1. Human-Object Interaction (HOI) Recognition

HICO-DET [8] is a dataset consisting of more than 150,000 human-object pair annotations. We split this dataset into a training set and a test set of 117,871 and 33,405, respectively. Furthermore, it contains 80 classes of objects, 117 types of actions, and 600 interaction types (including no interactions for human activity recognition). HICO-DET is one of the most primarily used datasets in HOI detection tasks. Another such dataset is the V-COCO which contains 2,533 training images, 2,867 for validation, 4,946 test images, and only 24 unique action classes.

3.2. Video summarization

UCF Crimes [38] is a large-scale dataset that consists of 128 hours of videos. It contains 1900 long and untrimmed real-world surveillance videos which show different criminal activities like Burglary, Arrest, Assault, etc. This dataset mainly has two tasks–detecting anomalies in videos and classifying suspicious behavior (or crime-based activity) from the video into any available action classes. We use a subset of the UCF Crimes dataset with only 300 videos (due to computation limitations) to evaluate the models (depicted in section 5.1). We generated ground-truth summaries of these videos by watching the videos for 32 hours, with the following classes (Arrest, Arson, Assault, Burglary, Explosion, Normal, Road Accidents, Robbery, Shooting, Shoplifting, and Vandalism). We used these to evaluate models and for them to function as a dataset for future applications.

3.3. Text classification

A Text-based classifier classifies the video captions generated. The dataset for training the NLP module has descriptions of crime scenes in the present tense (from the third person view) and non-criminal activity descriptive summaries. For criminal activities, the ‘incident description’ section of DPS crime alerts has been scraped from the DPS website [3] using the BeautifulSoup module [31], a total of 212 reports. We augmented the generated data to include multiple permutations of the words–‘man’ and ‘woman’ instead of ‘suspect’ and ‘victim.’

For non-criminal activities, we extracted 7985 transcripts from the CHARADES dataset [35], where each transcript is one sentence long and describes a human activity. We merged three transcripts to represent one activity to make the length comparable to summaries in the suspicious class, resulting in 2661 activities. This merge does not cause a problem because all activities of the CHARADES dataset can occur in conjunction with each other (without inconsistencies) as they are all individual activities. Moreover, we converted everything to the present tense as our generated ground truth video summaries have present tense. We picked approximately 408 summaries from this generated text corpus, and then used them as samples for non-suspicious activities to fine-tune the pre-trained BERT-base-uncased model.

Further, we added 250 criminal activity descriptions (label ‘1’) from the generated GloVe embeddings-based summaries in UCF-Crime (section 3.2) and 50 summaries for non-suspicious activities (label ‘0’) descriptions to the NLP text corpus for training the classifier. Hence, concluding our text corpus for fine-tuning the NLP text classifier with 920 textual summaries (out of which 445 are crime-based and 475 are normal activities).

4. Proposed Methodology

Figure 3 and figure 4 represent the different architectures that this research proposes. Figure 3 (BMT+Par HOI+NMS) proves to be suboptimal architecture, inferred from the results obtained in tables 3 and 5. We discuss this architecture in detail in subsection 6.2. Instead, we discuss BMT+Seq HOI+NMS (Figure 5) in much more depth in this section. Here, the NMS. In this model, the Human-Object Interaction module replaces the I3D model features in a Sequential fashion. Further, this model utilizes the concept of Non-}

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 footnotes:

 1. We plan to make this dataset publicly available for future analysis.
 2. All activities are taken in the present tense (using the tenseFlow (https://github.com/bendichter/tenseflow) (accessed: May 8, 2022)) to maintain symmetry between both kinds of descriptions.
 3. Stop words are removed and all sentences contain either ‘man’ or ‘woman’ and not ‘a person’.

References:

1. HICO-DET [8]
2. UCF Crimes [38]
3. DPS crime alerts [3]
4. CHARADES dataset [35]
5. V-COCO
6. BERT-base-uncased
7. CDN-L (R50)
8. CDN-B (R50)
9. CDN-S (R50)
10. UPT-base
11. QAHOI-Tiny
12. QAHOI-Base+
13. QAHOI-Large+
14. DE-TR (fine-tuned)
| Video class | Created summaries |
|-------------|------------------|
| Normal      | Cars are parked on the side of the road. Two men enter a building. An old man passes by. |
| Burglary    | A man wearing a helmet comes in front of a door of a house. Then, he tries to unlock the door. After several attempts, he fails to open the door and leaves the area. |
| Assault     | A man wearing a white shirt and carrying a bag comes and starts beating a man in blue shirt. Some people come forward to stop it. |
| Shooting    | A car is seen standing at the side of a road. Another car comes and a person inside the car shoots at the parked car. After that, the second car leaves and the man inside the parked car comes out. |
| Fighting    | Two young men wearing white shirts start fighting with a man in a suit. They hit him with a chair and kick him. The man wearing the suit also fights back. Some other people then join and try to control the fight. Finally, both the parties leave the area. |
| Shoplifting | A group of men enter a shop. They take some items from the shop. Some people inside the shop run away. Then, they leave the shop one by one. |
| Vandalism   | A car parks on the road. Two men walk toward the car. One man stops next to the car. The man kicks the car. Two men continue walking. |
| Arson       | A man is seen in a garage. He sets one of the cars on fire and runs away. Multiple cars catch fire and start burning. The cars are severely damaged. |
| Robbery     | A man wearing a white hat and black shirt comes in and aims at an employee at the cash counter. The employee gives away the entire cash to the man. |
| Arrest      | Two men come in a bike and one of them tries to get inside a building. Some officers stop him and the man starts fighting them. Finally, the officers arrest him. |

Table 2. A sample of author-created ground truth summaries for the UCF-Crime dataset

Maximum Suppression (NMS; given in more detail in Supplementary B.1) based on the Spatio-temporal dimension of the video.

We support the Sequential architecture as it accumulates the gradients during training and generates Optical Flow (using time-sensitive Intersection-over-Union discussed) and RGB (as depicted in figure 2) feature outputs. The object query of the Proposal Generator yields the RGB features, which then clip the videos into subsequences of videos to be encoded and decoded by BMT encoder-decoder architecture. Further, the Decoder architecture uses the encoded features from the trained Bi-Modal Attention in the Encoder layer to understand (decode) the feature vectors using a combination of self-Attention layers and GloVe embeddings to the BiModal Attention layer. For this task, we have leveraged several engineering and novel research techniques in this pipeline, as represented in figure 3. This process of encoding and decoding repeats N times until all the Optical Flow features and the RGB features are encoded and decoded to give a sequence of words, which is the required caption for the video. These are as follows.

1. Selective feature engineering for Audio-based VGGish where they were not available (videos without audio are assigned 0-valued tensors) as UCF-Crime is a dataset that is predominantly audio-less;
2. Non-Maximum Suppression thresholding of the time-Intersection-over-Union (tIoU) leveraged from the previous research related to BMT [16];
3. Parallel and Sequential HOI-model trained in parts (training of decoder and encoder of the model occurs separately to each other) using 20 % HICO-DET dataset (as depicted in figures 3 and 4).

Video Summarization is implemented using BMT (Bi-modal Transformers) [16] by leveraging HOI embeddings (instead of I3D extracted using the PWC-NET model [7]) and selective VGG encoding for the audio information. As mentioned earlier, we use selective audio tensors because videos may or may not have sounds that lead the model to propagate blank (or zero) tensors with the same shape as would have been sent if there was audio present in the video. This configuration occurs because most surveillance videos do not have any audio component. This audio-less behavior of surveillance feeds was evident in the UCF-crime dataset, where most videos did not contain audio. As the University of Central Florida compiled the UCF-Crime dataset, where the law selectively prohibits recording audio in surveillance feeds, it is easy to figure out why the UCF-Crime has videos without little to no audio component. For evaluation, we created a separate dataset by checking the videos from the

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5 This is due to the US Code Title XVIII Section 2510 which concerns user privacy and prevents anyone from recording audio without user consent. It states that “verbal communication between two people believing that their conversation is not being intercepted is justifiable reason to assume it is not being recorded”
subset of the UCF-Crime dataset (sample depicted in Table 6).

**RGB Feature Extraction based on HOI** We tested models like DE-TR, UPT, CDN, and QAHOI for comparative analysis (depicted in table 1 and figure 5). We used DE-TR primarily due to its good mAP (mean-Average Precision) discussed further in B.4 for higher sampling rates. But, it is vital to understand that DE-TR isn’t the top state-of-the-art model in terms of mAP. A Sampling rate of around 35 frames/second gives good results for the DE-TR model, whereas the UPT model works best around the sampling rate of 25 frames/sec. Further, models like CDN and QAHOI — models in the top-5 state-of-the-art for Human-Object-Interaction, sample frames at a rate of about 15 frames/sec, and 10 frames/sec (at best), respectively. These models were evaluated on 2 V100 and 2 A100 GPUs and took about 5 hours 42 minutes and 7 hours 17 minutes, respectively. Hence, due to the low sampling rate of the QAHOI, CDN, and UPT models, we trained the comparatively faster DE-TR for 1000 epochs for 20% of the HICO-DET dataset. This model training required us 52 hours on 2 A100 GPUs. This model was later used to generate the flow files and RGB files (similar to the i3D model in the BMT architecture) to ensure the consistency of the model.

Due to issues with the summaries generated from the Vanilla BMT model [10] (Table 6), the pipeline suffers from incorrect classifications (False Positives and False Negatives). These false detections can cause problems in monitoring surveillance videos for criminal activities. Hence, we proposed earlier to use transformer-based architecture for recognizing Human-Object triplets. This HOI model replacement ensures that summaries capture the feature representations of the Human-Object-Interactions that the following works—Multi-modal Dense Video Captioning model [17] and the Bi-Modal Transformer [16], fail to capture. Then text-generation models like [28] are used in the Decoder Layer to generate a summary from the captions obtained with timestamps. This approach increases the evaluation score of our model on various metrics such as BLEU@1, BLEU@2, BLEU@3, BLEU@4, and METEOR.

**Text classification:** We fine-tune a pre-trained BERT model [10] on the activity dataset (described in section 3.3). We used the BMT-generated summaries for inference in the activity dataset, which comprises approximately 920 (out of which 445 are crime-based and 475 are normal activities). We used the ‘BERT-based-uncased’ model from the Transformers library [3] for the model and embedding layer (depicted in figure 3 and figure 4). The representations are fed into a Gated-Recurrent Unit (GRU) for performing text classification of criminal activity descriptions. The task of the model is to classify the activity. We train this Bi-directional Gated BERT for two epochs with four layers, 256 hidden dimensions, 15% dropout, and an Adam optimizer (1×10^-4 learning rate). The model outputs a binary label where ‘1’ stands for suspicious activity, whereas ‘0’ represents non-suspicious activities.

We obtained optimal scores on the generated summaries when utilizing the BMT+seq HOI+NMS, as observed in Table 5. Further, the NMS value used here is 0.47 (based on Table 4). Table 5 lists various metrics for evaluating different models. This array of metric evaluations is because not a single (standalone) metric can help with which model performs better. This behavior can be due to the objective nature of these metrics that fail to attribute to the subjective nature of the natural language generation of high-priority applications such as suspicious activity detection using summaries. Hence, the various metrics for evaluating our model against the current state-of-the-art models.

5. Evaluation and Results

This section evaluates the proposed methodology and states the results associated with this research. These results are then expanded by a comparative analysis later in Section 6.

### 5.1. Dense Video Captioning

The evaluation of MDVC and BMT on ActivityNet Captions [22] was performed by [17] (represented in table 5). Table 3 describes these BLEU (for uni-gram (BLEU@1), bi-gram (BLEU@2), tri-gram (BLEU@3), and quad-gram (BLEU@4)) and METEOR between the output summarizations on a subset of UCF-Crime. Refer to [B.3] and [B.4] for a detailed explanation of BLEU and METEOR scores. Table 3 demonstrates a sample of summaries generated by the Vanilla BMT, BMT+Seq HOI+NMS, and BMT+Far HOI+NMS. As we discussed earlier, the DE-TR model generates a two-Stream output of Optical Flow and RGB features, as its Sampling rate is comparatively faster when compared to all other HOI models.

### 5.2. Text classification

The BERT-based cased and uncased text classifier uses Binary Classification Accuracy for evaluation. We fine-tuned the pre-trained BERT-base-uncase embeddings and model to a training accuracy of 97.29% on the total textual corpus (divided into training and testing sets in a 7:3 ratio). The 7:3 split preserved a similar distribution for suspicious (315 for training and 135 for testing) and non-suspicious activities (330 for training and 145 for testing) as the complete dataset. This model achieved a testing accuracy of 96.84% for this configuration of data split.
Table 3. A comparative analysis of BLEU and METEOR scores between generated summaries and ground truth summaries on UCF-Crime dataset for the ground truth generated.

| Metric            | BLEU@1 | BLEU@2 | BLEU@3 | BLEU@4 | METEOR |
|-------------------|--------|--------|--------|--------|--------|
| Vanilla BMT       | 10.47  | 5.43   | 0.114  | 0.053  | 13.22  |
| BMT+NMS           | 12.43  | 6.96   | 0.39   | 0.018  | 13.79  |
| BMT+Par HOI       | 8.32   | 4.31   | 0.29   | 0.056  | 11.65  |
| BMT+Par HOI+NMS   | 14.43  | 5.64   | 1.25   | 0.37   | 14.80  |
| BMT + Seq HOI + NMS | 14.49  | 7.03   | 2.54   | 1.19   | 15.05  |

6. Comparative Analysis

6.1. Non-Maximum Suppression (NMS) values

In this research, a genetic algorithm optimizes the tuning of NMS threshold values for different temporal Intersection-over-union (tIoU). The NMS values were selected for a pre-trained model and changed subsequently for each generation of parents (over five generations) based on the fitness score (here, BLEU@1). The NMS Threshold of 0.47 was achieved for Mutation parameters of [0.01, 0.03, 0.05, 0.07, 0.1] added based on a Gaussian probability distribution and randomly used for each parent over each generation with only 10% UCF-Crime dataset on an NVIDIA A100 GPU for approximately 92 hours. Table 4 represents the top 8 results for the exploration of NMS thresholds. Since traditional exploratory analysis can lead to a local extremum, using a Genetic Algorithm imposes a meta-heuristic on the NMS Threshold search that mitigates this problem. It is also important to note that other meta-heuristic search techniques might work even better for the same problem, but a comprehensive discussion is beyond the scope of this research.

6.2. Evaluating on ActivityNet Captions dataset

Table 5 represents the values obtained using only a 25% subset of the ActivityNet Captions dataset for dense captions [22]. We observe the start and end times of any activity demarcate its corresponding caption (depicted in figure 2) for all the models in table 5. It is important to note that the ActivityNet Captions dataset can have audio, hence the VGGish model was kept untouched during the training of the DETR model along with the Encoder Layer of the BMT+Seq HOI+NMS and BMT+Par HOI+NMS models.

Comparing Sequential HOI with Parallel HOI: We observe that the BMT + Seq HOI + NMS outperforms the
Table 4. A comparison of BLEU scores for different NMS values based on Genetic Optimization for 5 generations

| NMS thresholds | 0.1 | 0.3 | 0.35 | 0.45 | **0.47 (best)** | 0.5 | 0.7 | 0.9 |
|----------------|-----|-----|------|------|-----------------|-----|-----|-----|
| **BLEU@1 scores** | 12.44 | 12.57 | 13.44 | 13.12 | 13.97 | 12.41 | 12.11 | 11.17 |

Figure 4. Representation of Model architecture of the BMT+Par HOI+NMS utilized for the Comparative Analysis

BMT+Par HOI+NMS. This behavior occurs primarily because the Parallel HOI model creates an additional self-attention + proposal head pair (shown in figure 4). This pair (self-attention + proposal head) leads to redundant feature representations that the NMS should have mitigated. Due to this, the vital feature representations vanish due to the high bias that the model learns due to redundant feature representations. But, the Sequential flow replaces the I3D model with the DE-TR (or HOI) model as the primary choice of feature extraction (discussed in the methodology). Hence, this sequential two-stream output of HOI-based Optical Flow and HOI-based RGB feature allows the model to attend to the Human-Object-Interaction feature representations more efficiently and comprehensively leverage the Proposal Generator of the BMT (by using Proposal Heads). Table 3 suggests that the Sequential Flow pipeline outperforms the Parallel flow pipeline in all metrics (namely, BLEU@1, BLEU@2, BLEU@3, BLEU@4, and METEOR, etc.). Table 5 suggests a similar conclusion for the ActivityNet data analysis.

7. Dataset Limitations

This section contributes literature on the technical limitations of the datasets used in real-time surveillance settings (with a focus on ML and Computer Vision) based on the ActivityNet Captions and UCF-Crime datasets. We also discuss the general limitations of a suspicious activity detection model.

1. The **size of the training and evaluation data** (in both ActivityNet and UCF-Crime) was limited to fractions of the original video dataset. The distribution of the training and evaluation set (in terms of Crime classes and length of the videos) followed the original dataset. This undersampling ensured efficient utilization of limited computational resources;
2. The **lack of an audio component** in surveillance feeds severely limits the capabilities of the dataset to work in real-time surveillance applications like crime detection;
3. The **low resolution** of real-time surveillance data can lead to overarching concerns while training Computer Vision models. For instance, in videos related to Vandalism or Arson in UCF-Crime, the activity of a person starting a fire was seldom detected by the encoder-decoder model due to how fires start under different circumstances;
4. The scarcity of multi-view stereo data sources for real-time surveillance can mitigate the problems of
Table 5. A comparative analysis of the models for dense captioning evaluation on ActivityNet Captions dataset. Here, only 25% of the dataset was used for evaluation purposes.

| Model                        | BLEU@1 | BLEU@2 | BLEU@3 | BLEU@4 | METEOR |
|------------------------------|--------|--------|--------|--------|--------|
| MDVC [17]                    | 12.13  | 9.34   | 4.52   | 1.98   | 11.07  |
| BMT [16]                     | 11.12  | 8.71   | 4.63   | 1.99   | 10.90  |
| TSP [1]                      | 11.93  | 9.1    | 4.02   | 1.99   | 8.53   |
| PDVC (using TSP) [42]        | 13.84  | 9.87   | 4.47   | 2.01   | 8.94   |
| Bidirectional + Infra-Caption [36] | 12.71  | 10.33  | 5.11   | 2.72   | 11.28  |
| ADV-Inf + Global [20]        | 14.64  | 12.38  | 10.74  | 9.45   | 16.36  |
| BMT+NMS ($\phi = 0.47$)     | 13.75  | 9.71   | 4.27   | 2.01   | 12.99  |
| BMT+Par HOI+NMS ($\phi = 0.47$) | 12.43  | 8.29   | 4.26   | 1.99   | 12.47  |
| BMT+Seq HOI+NMS ($\phi = 0.47$) | 14.78  | 12.73  | 10.91  | 7.11   | 16.27  |

8. Ethical Considerations

This section discusses a few ethical considerations related to the dataset and the application discussed.

1. Suspicious behavior is intrinsically diverse. This diversity leaves a vast scope of deliberation regarding the validation of results. Due to the unprecedented nature of the context in which the suspicious activity occurs and the possibility of a previously unknown suspicious activity, it is vital to subject the model to regular revisions and checks;
2. Both false positive and false negative results are counterproductive for real-world scenarios of detecting suspicious activities. False Positives occur when a non-suspicious activity is predicted as suspicious behavior, whereas False Negatives occur due to the prediction of suspicious activities as non-suspicious;
3. The dataset curated by the authors represents a specific sample of crimes (discussed in section 3) and is not representative of the entire population. The dataset (that the authors created) aimed at demonstrating the working of the proposed modification approach, and the results can be highly variable when deployed on a large-scale basis.

9. Conclusion and Discussions

This paper introduced a new architecture for detecting suspicious activities in videos—by combining a Human-Object interaction model with a Dense Video Captioning model to generate Summaries. It further contributed two new datasets—ground truth captions for the UCF Crime dataset and the dataset for text classification of suspicious from non-suspicious activities.

Our work also discusses the drawbacks of using the DETR model in parallel for the first time and compares it with a similar Sequential contemporary for Dense Video Captioning using BMT. We achieved this by using the same model in a sequential form in a two-stream approach to replace the existing i3D features that formed the basis of the Vanilla BMT. This research also emphasized evaluating the model trained to other state-of-the-art models, and this model outperformed most of the models (represented by table 5). We obtained these conclusive results due to many practices employed while modifying the pre-existing BMT architecture. These practices included the usage of NMS thresholding (to get a disjoint set of image sequences), setting 0-tensors (for blank audio components in videos in UCF-crime dataset while training), searching the optimal NMS threshold (by use of Genetic Algorithms), and comparing various BMT architectures.

Further, we plan to work on possible modifications to this model architecture to extract audio features that have not been utilized optimally due to the sub-optimal VGG architecture (discussed in more detail in [16]). We further intend to compare various architectures defined in table 5 based on a two-stream approach with a faster sampling rate to understand the impacts on BLEU and METEOR scores. Conclusively, we can enhance video resolution by utilizing super-resolution models to get even better summaries from the models. And we also intend to explore other hyperparameter optimization techniques for the NMS threshold and work on the Optical Flow output (from NMS+Seq HOI+BMT) by leveraging modern techniques proposed by MODETR [26]. We further intend to explore our approach for mixed-modality datasets that contain both audio and videos after leveraging domain adaptation for videos (with audio) to prevent violation of any legal terms.
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A. Appendix

This section describes the technical implementation of the three different models (DE-TR for HOI Detection, BMT for Video Summarization, and GRU-based BERT for Text Classification), and section B discusses the metrics leveraged for this study. describes the metrics leveraged for this study. All the model implementations were in PyTorch and heavily utilized code from GitHub repositories of the origin work.

A.1. DE-TR for HOI Detection

As mentioned earlier, we trained the pre-trained DE-TR (or Detection Transformer model) on a subset of HICO-DET (19% of the dataset) for approximately 52 hours on 2 A100 GPUs. It has a Sampling Rate of 35 fps for inference when on NVIDIA GTX 1060. The two-stream output (Optical Flow and RGB) that we tuned it for is the primary cause for this extreme compute consumption. We set a learning rate of $1e^{-4}$, batch size of 2, weight decay of $1e^{-4}$, and backbone learning rate of $1e^{-4}$ for 100 epochs with early
stopping of 10 for this implementation. Further, we used the default backbone of ResNet-50, and two workers were used (as the number of GPUs was 2).

A.2. BMT for Video-Summarization

We trained the BMT in a disjoint way. First, we kept the VGGish model weights the same (used in the official GitHub implementation). We first fine-tuned the whole Caption Generator (Encoder-Decoder) with DE-TR (discussed earlier in A.1), as the authors suggested in the GitHub implementation (for i3D), and then fine-tuned the Proposal Generator. For training the Caption Generator, we used a subset of the UCF-Crime dataset (as discussed earlier) for 62 hours with a learning rate of $1e^{-4}$ and a batch size of 16. We used start-times and end-times as labels for the proposals that the authors generated (using a combination of MDVC and BMT [17, 16]). These proposal times were matched with each sentence of our annotated data points and then used to train the Proposal Generator. We used the same learning rate and a batch size of 8 for fine-tuning the proposal generator. Here, we added a condition to change the noisy or random audio signals to 0-tensors. Note that these steps stayed the same for BMT+Seq HOI+NMS (figure 3) and BMT+Par HOI+NMS (figure 4), apart from the modifications in the model architecture. We did not use the 0-audio-tensors while evaluating the models on ActivityNet Captions dataset. Hence, the results are comparable to the Global ADV-INF model in table 5.

A.3. GRU-based BERT for Text Classification

We trained GRU-based BERT based on the dataset discussed in section A.3. Here, we used a combination of 408 summaries modified from CHARADES (according to earlier details) and 212 from USC DPS reports. This dataset was then augmented with 300 text summaries from the UCF-Crime dataset (250 Suspicious and 50 Non-Suspicious), leading to a total of 920 data points (445 Suspicious and 475 Non-suspicious). This combined dataset was split in a 7:3 ratio. Then, we used Adam with a learning rate of $1e^{-4}$ and a batch size of 8 for fine-tuning the BMT model. We added a condition to change the noisy or random audio signals to 0-tensors. Note that these steps stayed the same for BMT+Seq HOI+NMS (figure 3) and BMT+Par HOI+NMS (figure 4), apart from the modifications in the model architecture. We did not use the 0-audio-tensors while evaluating the models on ActivityNet Captions dataset. Hence, the results are comparable to the Global ADV-INF model in table 5.

B. Supplemental Material

B.1. Non-Maximum Suppression (NMS) and time-Intersection-over-Union (tIOU)

The objects in the image can be of different sizes and shapes, and to capture each of these perfectly, the object detection algorithms create multiple bounding boxes. NMS is a common technique in Object Detection (used in this case) where it selects the few best bounding boxes based on a threshold. In other words, non-max suppression (or non-maximum suppression or NMS) helps to find the best bounding box for an object and reject or ‘suppress’ all other bounding boxes.

In other words, NMS is a technique to select one entity out of many overlapping entities. As we know, various frames in a video can have a high degree of overlap, so NMS is employed to select frames with a lower degree (only here) of overlap. Hence, NMS helps segment frames unrelated to each other and leads to better results when decoding feature representations for generating captions (due to better clipping obtained as in figure 3). This NMS threshold takes two things into account.

1. Objectiveness Score (given by the model)
2. Overlap or IOU of the bounding boxes (for Human and Object Detection) on a frame-by-frame basis

An NMS threshold addresses the RGB and Optical Flow features. An NMS threshold addresses the RGB and Optical Flow features obtained to get better segments of frames for better captions.

Hence, we define a term--tIOU (time-Intersection-over-Union), which measures the overlap between the frames and tries to keep unrelated Frames in different segments and similar ones in one Segment. When defining an NMS threshold, we are querying all the Segments with an NMS threshold higher than a given value. On the contrary, Frame pairs with lower tIoU get divided into different Segments. This segregation results in different Segments in text summaries.

B.2. Average and Mean Average Precision

The Average Precision (or AP) is the most popular evaluation metric for object detection and human-object
interaction models. HOI tasks deal with a range of Intersection-over-Union (IoU) threshold values (different from tIOU discussed in B.1). AP is the weighted mean of precision values at these IoU thresholds. On the other hand, Mean Average Precision (mAP) is the average of the Average precision values for each output class and is the area under the Precision-Recall curve. This metric is closely related to the concepts of Confusion Matrix, Intersection-over-Union, Precision, and Recall. To calculate the Average Precision, the following are the steps.

1. Generate the prediction scores using the model
2. Convert the prediction scores to class labels
3. Calculate the confusion matrix—TP, FP, TN, FN
4. Calculate the precision and recall metrics
5. Calculate the area under the precision-recall curve
6. Measure the average precision

And after taking the mean of the calculated AP, we obtain the mAP (Mean Average Precision) value discussed earlier.

B.3. BLEU score

BLEU (Bilingual Evaluation Understudy) is a metric for evaluating machine-translated pieces of text. It has values between 0 and 1 that score the similarity of a machine-translated text to some high-quality reference translated texts.
Figure 6. Representing tIoU (time-Intersection-over-Union) and NMS (Non-Maximum Suppression) frame-by-frame from a video from CHAIRS [19]. Here, the Blue anchors define a segmentation of frames in the video where corresponding frame-pairs have higher NMS threshold. With lower NMS threshold, less number of segments contain several frames while with a higher NMS threshold, more number of segments contain less number of frames.

A higher BLEU score implies better translations or summarizations. Here, the BLEU score is a percentage of values from 100 instead of a value from 1. Further, the values (for instance, BLEU@n refers to the BLEU score for individual BLEU values for n-grams) in the official definition of BLEU are not a single value of BLEU but a whole family of them parametrized by the weighting vector. In other words, it is the weighted Geometric Mean of the modified n-gram precision. The BLEU score (eq. 1) is the product of the weighted GM and the brevity penalty (penalizing short text generation to contain words in the original/ground-truth corpus).

$$BP = e^{-(r/c-1)^+}$$  \hspace{1cm} (1)

Here, \((r/c-1)^+\) refers to the positive part of this term. \(r\) is the effective length of the ground-truth corpus. Hence, when \(r < c\), no penalization occurs, and BP is 1.

**B.4. METEOR Score**

METEOR is another metric for evaluating machine-translated texts based on the harmonic mean of the Precision and Recall of Unigrams, where Precision values are weighted more than Recall values. Similar to BLEU, higher METEOR scores imply better machine translations. This metric can also account for the problems in the BLEU metric. For instance, Word stems and synonyms are not handled well in BLEU (discussed above). This metric is of significant importance as it has a higher correlation with human-readable generated texts. Eq. 2 is used to calculate this metric.

$$M = F_{hmwp} \cdot (1 - p)$$  \hspace{1cm} (2)

Here, \(M\) is the METEOR score, \(F_{hmwp}\) is the harmonic mean in which Precision (\(P\)) is weighted ten times more than the Recall (\(R\)), and has been depicted by eq. 3. \(p\) designates the penalty incurred when considering longer text segments. This penalty is higher if more mappings are incongruent with Segments of texts in the original (expected) text summaries. This penalty is given by eq. 4.

$$F_{hmwp} = \frac{10 \cdot P \cdot R}{R + 9 \cdot P}$$ \hspace{1cm} (3)

Here, \(P\) is Precision, and \(R\) is the Recall of the model used.

$$F_{hmwp} = 0.5 \cdot \left(\frac{c}{u_m}\right)^3$$ \hspace{1cm} (4)

Here, \(u_m\) is the number of mapped unigrams, and \(c\) is the number of segments mapped for these.