Any Object is a Potential Weapon! Weaponized Violence Detection using Salient Image

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Abstract—In every connected smart city around the world, CCTVs have played a pivotal role in enforcing the safety and security of the citizens by recording unlawful activities for the authorities to take action. To ensure the efficiency and effectiveness of CCTVs in this domain, different DNN architectures were created and used by researchers and developers to either detect violence or detect weapons using bounding boxes or masks. These weapons are limited to guns, knives, and other obvious handheld weapons. To remove these limits and detect weapons more efficiently, non-weaponized violence footage from CCTV must be distinguishable from weaponized ones. Since there are no current datasets that are tailored to this purpose of generalizability in weaponized violence detection, we introduced a new dataset that contains videos depicting weaponized violence, non-weaponized violence, and non-violent events. We also propose a novel data-centric method that arranges video frames into salient images while minimizing information loss for comfortable inference by SOTA image classifiers. This was done to simplify video classification tasks and optimize inference latency to improve sustainability in smart cities. Our experiments show that Image Classifiers can efficiently detect and distinguish violence with weapons from violence without weapons with performances as high as 99%, which are comparable with current SOTA 3D networks for action recognition and video classification.

Index Terms—Action Recognition, Violence Detection, Weaponized Violence Detection, Smart Cities, Deep Neural Networks, Signal Processing

I. INTRODUCTION

Cases of violence and gang-related activities in a city could be rampant and serious especially if there is no way the required authorities can get to the scene in time to curb further destruction. Some of these violent activities could result in the loss of lives and properties especially when weapons are used. Events and cases of road rage violence, gang-related violence, and other random acts of violent crimes have been reported too late for the authorities to be able to do something about it [5]–[7].

While the growth of surveillance systems has since helped authorities find culprits and instigators from recordings, the time taken from the initiation of the crime to the detection, search and arrest is far too much. There came the need for automated detection and authorities’ signal to reduce turnaround and throughput time. Ever since the breakthrough of AlexNet in the ImageNet 2012 competition [8], DNNs have been the go-to AI technology for automating such tasks. Leveraging DNNs and other AI techniques for violence detection in smart cities around the world has helped in safeguarding the lives and properties of people.

Current work in the violence detection domain leveraged spatio-temporal models to detect violence in videos. However, violence could come in different forms; two individuals can be involved in a heated argument and start shoving each other. At that same instance, two or more individuals might be involved in a gun fight somewhere else. These two events belong to the general category of violence, and when automatically detected, would be reported with similar priority. This brings about the need for detecting weapons in surveillance coverage of violent events.

To solve this, research carried out focused on identifying weapons in scenes using object detection models. However, the datasets currently used in the weapon detection domain are limited to specific weapons such as knives, guns, etc. While the intentions are justifiable (since these weapons are the most used weapons), it could be wrong to limit the scope or boundaries of weapons. Any object could serve as a weapon, as long as it could be deadly when applied on an individual or a property. This brings about the need to conduct further research for more efficient open-world weapon detection.

Furthermore, spatio-temporal models such as C3D, ConvLSTM used for violence detection, and DNNs used for weapons detection (i.e., YOLO, RCNN) consume a lot of energy due to the large amounts of computations needed for state-of-the-art performance. This increases the carbon footprints in smart societies. Our goal however is to solve all of the explained issues, with a simple image classifier and contribute to a major goal of smart cities which is sustainability. To achieve this, we contributed the following:

- We are the first to approach violence and weaponized violence detection as a single task. To do this, we created a new dataset called the Smart-City CCTV Violence Detection (SCVD) dataset which strictly contains CCTV footage of weaponized and non-weaponized violence. This means that our dataset could assist DNNs to learn the distribution of weapons in CCTV recordings.

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• We propose a novel technique called Salient Image, which builds upon [1] to convert our video classification task to an image recognition task, thereby improving inference speed and model simplicity, thereby making us the first to treat 3D tasks from a 2D-perspective.

• We evaluated the performance of image classifiers on both Salient and Super Image approaches. The classifiers achieved better accuracy on salient arrangements ($\approx +2\%$) than the super arrangements on the Kinetics-400 dataset. This proves that the Salient image approach helps preserve more information within each video frame thereby leading to better feature extraction and optimized performance.

• We leverage multiple image classifiers and evaluated them using trade-offs to get the best architecture to achieve sustainability in smart cities. Our experiments show that our selected image classifiers achieve comparable results with I3D [3] and X3D [4], with our best classifier achieving inference $\approx 2.5 \times$ faster than X3D and $\approx 3.5 \times$ faster than I3D.

II. RELATED WORK

A. Weapon Detection

Object Detection is modeled as a classification task in which sliding windows of fixed sizes are taken from the input image at every possible location and fed into an image classifier for inference. There have been two main approaches to this computer vision task: YOLO [9] and RCNN [10]. Since the inception of both methods, research has gone into optimizing both methods either to achieve better performances (Mask RCNN [12], YOLO V3 [14]) or for faster inference (Faster RCNN [13], YOLO V2 [11]) or both (Fast RCNN [15], YOLOV4 [16], YOLOV7 [17]).

The typical workaround leverage the Faster RCNN object detection model to identify weapons and classify them [29], [30]. While [29] used transfer learning by taking a pre-trained Faster RCNN model to detect handheld guns in clustered scenes, [30] tried an ensemble method by combining Faster RCNN and Single Shot Detector [18] to identify and classify mostly guns and knives. [31] employed a pre-trained Yolo V4 on the same dataset as [30]. However, all of these methods cannot generalize to the vast options of objects which could easily be used as weapons. Also, none of these methods were trained on datasets containing CCTV footage, hence limiting the data distribution to other forms of videos.

B. Violence Detection

While there are multiple attempts on detecting weapons from videos only, there are works that aim to detect violence from videos and CCTV footage. For example, [32] used an image classifier (InceptionNet [38]) to detect violence in every frame from sports videos and movies. This results in slower inference and also poor generalization results as their method failed to learn temporal properties connecting frames within similar video embeddings. For their models to not lose temporal information, [25] and [33] used ConvLSTMs to detect violence in CCTVs. In ConvLSTMs, an image classifier is employed for spatial feature extraction while LSTMs learn the temporal information. [33] used a pre-trained ResNet50 model to extract spatial features from the video frames while [25] leveraged the VGG16 architecture. The extracted features are then concatenated with the latent features from the LSTM model. This results in models requiring a lot of computing resources.

In contrast to the above techniques, our goal is to create a data-centric approach that would enable image classifiers to learn both spatial and temporal features for efficient weaponized violence detection in CCTV videos. This is made possible by building upon the super image approach, which was first proposed in [1]. To the best of our knowledge, our work is the first attempt to achieve efficient and generalized weaponized and non-weaponized violence detection in CCTV footage depicting violence.

C. Super Image

Action Recognition for Video Classification tasks has become an active research area in recent years, as it plays a significant role in video understanding. While general approaches in this domain use 3D convolutions to classify videos either by using appearance [2], depth [3], [4], and body skeletons [19], [1] used a 2D image classifier (SIFAR). It was argued that instead of using big and hugely deep 3D networks for video action recognition tasks, a simple image classifier would work. For this to work, a technique that extracts frames from videos resizes these frames and combines them into a super image that involves both local (i.e., spatial information in a video frame) and global contexts (i.e., temporal dependencies across frames) was proposed. Their experiments gave promising results which proved that 2D image classifiers could give comparable results when compared to their 3D counterparts.

In this work, we build on this idea and attempt to design salient image, a simple but more effective variant of the super image, specifically for detecting weaponized and non-weaponized violence in videos captured by surveillance systems, especially those involving weapons. Since there is no current dataset that can be used for this task, we create SCVD, a novel dataset that contains distinctive videos of weaponized and non-weaponized violence in CCTVs.

III. DATASET

We propose the Smart-City CCTV Violence Detection (SCVD) Dataset, a new benchmark strictly containing CCTV footage showing weaponized violence and non-weaponized violence scenarios. The main goal of creating this dataset is to help AI models learn the degree of danger in chaotic events recorded by surveillance systems. Since current models used to identify violence are post-active by nature (the general
Table I

| Dataset         | Type       | Size           | Length/video (sec) | Annotation | Violence | Weapons | Characteristics | Scenario       |
|-----------------|------------|----------------|-------------------|------------|----------|---------|-----------------|----------------|
| NTU CCTV-Fights | Video      | 1000 videos    | 5-720             | Frame      | ✓        | ✗       | CCTV + Mobile    | Natural        |
| Hockey Fight    | Video      | 1000 videos    | 1-2               | Video      | ✓        | ✗       | Aerial Camera    | Hockey Games   |
| RLVS [25]       | Video      | 2000 videos    | 5-15              | Video      | ✓        | ✗       | CCTV + Mobile    | Natural        |
| RWF-2000 [26]   | Video      | 2000 videos    | 5                 | Video      | ✓        | ✗       | CCTV Surveillance|                |
| Sohas [27]      | Image      | 3255 images    | N/A               | Image      | ✗        | ✓        | Captured Images  | Demonstrations |
| WVD [28]        | Video      | 168 videos     | 10-72             | Video      | ✓        | ✓        | Synthetic        | Computer Games |
| Ours            | Video      | 500 videos     | 5-10              | Video      | ✓        | ✓        | CCTV Surveillance|                |

Table I: Comparisons between the SCVD and the previous datasets.

Fig. 1. Salient Image: A sequence of video frames gotten from a CCTV surveillance system are first rearranged into a salient image based on a 5 × 3 or 3 × 2 spatial arrangement, and then fed into a CNN architecture for training and recognition.

design is to alert the authorities after violence is detected), we felt that setting priorities and trying to identify weapons in violent events would hasten the right authorities to try to curb further destruction. Violent events in which weapons are used shouldn’t be attended to in the same form as arguments and fist fights are attended. There is always more damage caused when weapons are involved than when weapons are not involved.

Table I shows a summary of the comparison with other datasets. We considered datasets used to train DNNs to detect violence [22], [24]–[26] as well as datasets for weapons detection [27], [28]. The datasets currently in use for violence detection contained 1000 to 2000 videos which are annotated either at frame [22] or video level [24]–[26]. However, while these datasets only concentrated on violence detection, only [26] strictly used videos captured from CCTV surveillance systems. This makes the other datasets unsuitable as we try to limit the distribution of the videos to only surveillance.

To detect weapons in videos, Sohas [27] and WVD [28] were created. While Sohas contained images with bounding box annotations, WVD contained synthetic videos of length 10 to 72 seconds generated from the GTA-V computer game and annotated at the video level. Both Sohas and WVD contained guns, knives, and other well-known weapons, with the distribution not focused on surveillance. Since both datasets focus on only a limited number of weapons, they are also unsuitable for this task.

The most similar dataset to ours is the RWF-2000 [26]. It contains 2000 videos with a length of 5 seconds per video which are strictly collected from surveillance systems. However, the dataset only contains generalized violence without a distinctive reference to the type which contains weapons, making it also unsuitable for our task.

Our dataset was gotten by running an automated script that crawled through YouTube and downloaded the most related videos using a combination of geographical prompts. This was to ensure that the videos are not limited to just one location but generalized to most parts of the world. Also, there are videos recorded within buildings, as well as videos recorded outside, and from different CCTV sensors. The downloaded videos were 720p with frame dimensions of 1280 × 720. We had 500 videos left after cleaning the datasets to remove noisy videos and staged videos. These videos were then trimmed to get a length ranging from 5 to 10 seconds, annotated at the video level. There are three classes/folders present in the final dataset; Violence (V), Normal (N), and Weaponized Violence (WV) which contain videos with an arbitrary number of possible weapons to improve the performances of DNNs on weaponized violence classification.

IV. PROPOSED METHOD: SALIENT IMAGE

In a classic CNN architecture, the input to the convolutional layer is usually a single image with the object of interest mostly at the center of the image. As a result, the CNN learns the spatial context image by image without relations to the previous or next input. Since we are dealing with video understanding tasks, this approach is not the best option for video input, as each individual frame within a video is related to the frame before and after.
A. Frame Arrangements

With this in mind, [1] explored the possibility of merging multiple input frames from a video to form a super image (which contains both spatial and temporal information) before sending this input to the CNN. Experimenting using different frame combinations, it was found that a square formation (i.e., $4 \times 4$ arrangement) for merging the frames has the best performance as compared to linear (i.e., $16 \times 1$ arrangement) or rectangular (i.e., $8 \times 2$ arrangement) formations. For that to work, each frame was resized into a square shape (i.e., $224 \times 224$ frame size), then combined to form a square formation (i.e., $896 \times 896$ super image), and finally resized to get a $224 \times 224$ super image for input into the classifier.

The downside to the super image approach comes from the large amounts of added noise which comes from resizing every frame plus the final resizing to get the required input size. Resizing (downsizing) images also come with information loss which may hamper the performance of the model. We propose Salient Image to solve this issue. The main idea is to reduce the information loss in super images, by trying to achieve the optimal grid selection before resizing to get a salient image for input into the classifier.

The minimum number of frames along the $x$-axis, $n$ should be 2, and due to this, the minimum number of frames along the $y$-axis, $m$ should always be greater than 2 ($n \geq 2, m \geq 3$).

Since the final step of the salient image process is to resize the salient images to a dimension of $224 \times 224$, it is advisable to set $m$ and $n$ as small as possible, so that the input to the image classifiers would contain as much spatial and temporal information as possible. Resizing a very large salient arrangement; let’s say a $4320 \times 4320$ to $224 \times 224$ would remove as much information as possible for the image classifier to learn anything. Maximally, we advise that $m$ should be set to 5 while $n$ should be set to 3.

Using these considerations, we chose two optimal grid $m \times n$ selections; the maximal grid, $5 \times 3$ and the minimal grid $3 \times 2$. Combining them using these grid structures forms an almost-square shape and this helps in preserving the local and global information when the salient image is resized later for input into our chosen architectures (see Figure [1]).

**Note:** It is however possible for surveillance footage to come in other dimensions aside from the $1280 \times 720$. In such cases, the optimal choice for $m$ and $n$ should be dependent on the height $h$ and width $w$ such that:

$$\min(w_n - h_m) \quad (1)$$

where $n$ is the number of frames along the width (i.e., $x$-axis) and $m$ is the number of frames along the height (i.e., $y$-axis) so that:

$$w_n \approx h_m \quad (2)$$

Therefore, as opposed to Super Image, Salient Image reduces the amount of information loss by combining frames using an optimal grid selection before resizing to get a $224 \times 224$ salient image for input into the classifier.

B. Optimal Grid Selection

Since our SCVD dataset contains videos with frame dimensions of $1280 \times 720$, the following were considered in order to get our optimal grids:

- a $1 \times 1$ grid would give single frames of the original dimensions. This isn’t optimal as the temporal information we hope to get isn’t present in the arrangement.
- Since the height $h$ of the frames is smaller than the width $w$, for $w_n \approx h_m$, $m$ has to be greater than $n$ (i.e., $m > n$). For example, setting $m$ as 1 and $n$ as 3, the produced salient image dimensions will be $3840 \times 720$ and that’s far away from being as square as we want.

The choice of the optimizer is based on the general knowledge that SGDM ensures full convergence, compared to Adam. The SGD optimizer for parameter update is:

$$\partial w_t = w_t - \alpha \frac{\partial L}{\partial w_t} \quad (4)$$

where $w_t$ is the weight, $\partial w_{t+1}$ is the parameter being updated, $\alpha$ is the learning rate and $\frac{\partial L}{\partial w_t}$ is the partial derivative of the gradient. All networks were trained from scratch for 50 epochs, and the best test accuracies for each network were extracted and recorded along with their train loss values.

1https://github.com/tensorflow/tensorflow
2https://github.com/keras-team/keras
3https://github.com/pytorch/pytorch
4https://github.com/open-mmlab/mmaction2
TABLE II
MODEL PERFORMANCE ON DIFFERENT SALIENT AND SUPER IMAGE ARRANGEMENTS OF THE KINETICS-400 DATASET

| Method | # Input Frames | ResNet50 | ResNet101 | DenseNet121 |
|--------|----------------|----------|-----------|-------------|
| Salient 3 × 2 | 6 | 77.3 | 78.9 | 76.8 |
| Super 3 × 3 | 9 | 75.5 | 76.4 | 75.0 |
| Salient 5 × 3 | 15 | 76.1 | 77.2 | 75.3 |
| Super 4 × 4 | 16 | 74.5 | 75.9 | 74.2 |

B. Results

Salient Image vs Super Image: To prove that the Salient Image preserves information than the Super Image through its method of arrangement, we tested the performance of ResNet50, ResNet101, and DenseNet121 classifiers on different arrangements of 3 × 2 and 5 × 3 salient images against 3 × 3 and 4 × 4 super images using the Kinetics-400 Video Classification dataset [41]. These classifiers were pre-trained on the ImageNet-1K dataset.

The Kinetics-400 is an action recognition dataset of realistic action videos which were collected from YouTube. It contains 306,245 short-trimmed videos from 400 action categories. We trained each model for 200 epochs using the Adam optimizer with a learning rate of 1e-3, which decays by a value of 1e-1 every 70 epochs.

From the ablation carried out by [1], a square arrangement produced the best results. So, for a fair and direct comparison with our Salient arrangement, we experimented with Super image arrangements of 3 × 3 and 4 × 4 against Salient arrangements of 3 × 2 and 5 × 3 respectively.

The results from Table II show that each model performs better on the Salient arrangements than on the Super images by ≈ 2% while using lesser frames. Therefore, while the super image has done a great job of simplifying a video task by converting it into an image task, salient image arrangement based on the original video dimensions ensures more information preservation.

TABLE III
RESULTS GOTTEN FROM EXPERIMENTS USING DIFFERENT ARCHITECTURES ON THE 3 × 2 AND 5 × 3 SALIENT ARRANGEMENTS

| Salient Arrangement | Model | Test Accuracy (%) |
|---------------------|-------|-------------------|
| 3 × 2               | VGG19 [34] | 98.1              |
|                     | VGG16 [34] | 94.3              |
|                     | ResNet50 | 96.8              |
|                     | ResNet101 | 97.9              |
|                     | DenseNet121 | 98.6              |
|                     | EfficientNetB0 [37] | 84.0              |
|                     | InceptionV3 | 98.6              |
| 5 × 3               | VGG19 [34] | 98.0              |
|                     | VGG16 [34] | 96.4              |
|                     | ResNet50 | 96.5              |
|                     | ResNet101 | 91.9              |
|                     | DenseNet121 | 96.6              |
|                     | EfficientNetB0 [37] | 82.3              |
|                     | InceptionV3 | 94.1              |

Fig. 2. The F1-Score showing the performances of different architectures on each class in the SCVD dataset. Aside from the EfficientNetB0, the other models were able to capture the relationships and differences amongst the classes to give a good performance.

Image classifiers on Salient Image: We first trained the classifiers described in the environment subsection from scratch on the 3 × 2 and 5 × 3 salient images extracted from our SCVD dataset. From the results shown in Table III, the following were observed:

- The classifiers generally performed better on the 3 × 2 salient image arrangement than on the 5 × 3 salient arrangement. This proves our hypothesis that using larger values for m and n could lead to larger information loss for the classifiers to be able to learn the right information.

- The EfficientNetB0 model struggled to learn any information from both arrangements, while the VGG and DenseNet models performed better than the other networks on both arrangement. The ResNet50 also achieved good performances on both arrangements, while the ResNet101 struggled more on the 5 × 3 salient image.
To better understand these results, we calculated the F1-Score of each model on both salient arrangements (Figure 2). We also leverage the Grad-CAM tool [40], to show what neurons are activated by each architecture (Figures 3). The F1-Score for each class is given as:

$$F_{1k} = \frac{2(P_k \cdot R_k)}{P_k + R_k}$$  \hspace{1cm} (5)

where $k$ is the class we are evaluating the $F_1$ score for, $P_k$ is the precision for the class and $R_k$ is the recall. The F1-Score for both salient arrangements showed that the classifiers were able to achieve close to the same performances on each of the classes, except for the EfficientNetB0 which failed to understand the differences between the weaponized and non-weaponized classes.

From the GradCAM outputs as shown in Figure 3, we can conclude the following:

- All models aside from EfficientNetB0 are able to learn from each of the combined frames in both salient arrangements. The performances of the models on the $3 \times 2$ are generally better than those of the $5 \times 3$. This is because the frames in the $5 \times 3$ arrangements were too small after resizing from $3840 \times 3600$ to $224 \times 224$. This means some spatial information in each frame were lost, leaving just a small quantity for some of the used classifiers to find how they relate with the temporal counterparts.

- The VGG16 tries to learn individually from each frame in the $5 \times 3$ salient arrangement, which made it have the best performance on that arrangement. However, its performed marginally better on the $3 \times 2$, which further proves that more information is lost in larger salient arrangements.

- DenseNet121 and InceptionV3 had similar behaviour on the $3 \times 2$ arrangement; combining both spatial and temporal features from the stack of 6 frames, thereby having the most optimal performance of 98.6%.

Comparison with SOTA Methods: We compare the performances of image classifiers used by our method with two SOTA video classification methods based on convolutional neural networks; I3D and X3D. These models were pre-trained on the Kinetics-400 dataset. We select the best classifiers for each arrangement from our earlier experiments and loaded their pre-trained ImageNet1k versions for finetuning.

From Table IV we are able to show that the Salient image approach to video classification is able to match up with the performance of I3D and X3D. The maximum accuracy of 98.6% was achieved by Salient-ResNet50 on 6 frames, I3D-R50 on 16 frames, and X3D-M on 16 frames. However, the other image classifiers used by our method had similar accuracies while needing lesser frames and lesser inference time.

In a real-world scenario, while violence could extend for a longer period, the decision to inflict injury using a weapon might occur in a split second. Therefore, reporting violence as soon as a weapon is detected is essential to mitigating potential harm to lives. Using image classifiers on Salient images, therefore, beats the SOTA 3D methods, as these events are detected approximately $3.5 \times$ faster while still maintaining the same accuracy.

Sustainability in a Smart City Context In a Smart City context, however, one of our aims is to present tradeoffs to
consider when selecting a model to use for our weaponized violence detection task. These tradeoffs would specifically help reduce the carbon footprints of deep learning models and improve sustainability in smart cities.

From the results presented in Table IV the tradeoff lies in the intersection of the number of parameters for each model, accuracy, time, and fps. However, the goal will be to select a model with high performance while also maintaining a minimal time (which leads to faster inference). In mathematical terms, we aim to select the model which does the following:

\[
(i) \min(\theta_P, \theta_T) \quad \text{(6)}
\]

\[
(ii) \max(\theta_A, \theta_{F_{\text{min}}}) \quad \text{(7)}
\]

where \(\theta_P\) represents the model’s number of parameters, \(\theta_T\) stands for the average time taken for the model to infer, \(\theta_A\) is the model’s accuracy, and \(\theta_{F_{\text{min}}}\) is the minimum number of frames processed by the model per second.

Research has often linked the small number of parameters in models directly to faster inference time, but this is not always the case as DenseNet121 with a 7.04M number of parameters is slower than VGG16 with 134M. To regularize this uncertainty, other tradeoffs have to be considered. For example, the model’s accuracy has to be high enough to ensure safe deployment.

To also meet up with the demands of current video-capturing technologies and surveillance systems, inference time is also a very important tradeoff factor to be considered. Therefore, using the proposed tradeoffs would help promote a sustainable, smart, and safe society.

### VI. Conclusion

This work aims to detect weaponized and non-weaponized violence in surveillance systems, while also trying to remove the limits on the type of weapon used. Due to the lack of video datasets with weaponized violence classes, we created and proposed a novel video dataset; the Smart City Violence Detection (SCVD) Dataset. To further improve the efficiency of detecting these events, we presented Salient Image, a technique which converts the 3D video understanding task to a 2D perspective for input to selected image classifiers. Experiments show that the Salient Image minimizes information loss compared to Super Image [1], and achieves better results using Image Classifiers on the Kinetics-400 dataset. Further extensive experiments on the SCVD dataset shows that using a single efficient image classifier with our approach could match the performance of SOTA 3D models, while achieving faster inference time and processing more frames per second. Tradeoffs to reduce carbon footprints for improving the sustainability of smart cities were also discussed.

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### Table IV: Comparison with Other Approaches on the SCVD Dataset

| Model                  | # Input Frames | Param (M) | Accuracy (%) | Time (ms) min | min_fps | max_fps |
|------------------------|----------------|-----------|--------------|---------------|---------|---------|
| I3D-R50 [3]            | 8              | 47.0      | 98.1         | 428.8         | 15      | 24      |
| I3D-R50 [3]            | 16             | 47.0      | 98.6         | 374.4         | 36      | 45      |
| X3D-M [4]              | 8              | 3.8       | 98.4         | 311.5         | 24      | 30      |
| X3D-M [4]              | 16             | 3.8       | 98.6         | 268.0         | 45      | 60      |
| Salient-VGG16          | 6              | 134.27    | 98.2         | 547.2         | 36      | 45      |
| Salient-VGG16          | 15             | 134.27    | 97.9         | 547.2         | 36      | 45      |
| Salient-ResNet50       | 6              | 23.5      | 98.6         | 126.8         | 45      | 60      |
| Salient-ResNet50       | 15             | 23.5      | 98.6         | 126.8         | 45      | 60      |
| Salient-DenseNet121    | 6              | 7.04      | 98.4         | 167.9         | 24      | 30      |
| Salient-DenseNet121    | 15             | 7.04      | 98.1         | 177.4         | 80      | 90      |
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