

DeepSegmenter: Temporal Action Localization for Detecting Anomalies in Untrimmed Naturalistic Driving Videos

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Abstract

Identifying unusual driving behaviors exhibited by drivers during driving is essential for understanding driver behavior and the underlying causes of crashes. Previous studies have primarily approached this problem as a classification task, assuming that naturalistic driving videos come discretized. However, both activity segmentation and classification are required for this task due to the continuous nature of naturalistic driving videos. The current study therefore departs from conventional approaches and introduces a novel methodological framework, **DeepSegmenter**, that simultaneously performs activity segmentation and classification in a single framework. The proposed framework consists of four major modules namely Data Module, Activity Segmentation Module, Classification Module and Post-processing Module. Our proposed method won **8th place** in the 2023 AI City Challenge, Track 3, with an activity overlap score of **0.5426** on experimental validation data. The experimental results demonstrate the effectiveness, efficiency, and robustness of the proposed system. The code is available at <https://github.com/aboah1994/DeepSegment.git>.

1. Introduction

Driving is a complex activity that necessitates a high level of concentration and coordination. Even with the best intentions, drivers may engage in behaviors that can result in accidents, such as distracted driving, aggressive driv-



Figure 1. Cameras mounted on vehicle's dashboards to monitor drivers' behavior in a naturalistic environment.

ing, or driving while impaired. Our ability to identify and characterize these behaviors is essential for enhancing road safety and preventing traffic accidents. To do the aforementioned, a comprehensive dataset detailing different anomalous driving behaviors and differentiating them from safe driving actions is required.

The naturalistic driving dataset is one such dataset that has been used extensively to study unsafe driving behaviors. As shown in Fig. 1, naturalistic driving data refers to information collected from sensors or cameras mounted on vehicles as they are driven in real-world environments. This type of data contains a wealth of information about the driving task, including the actions of the driver and the context in which they are performed. This makes it possible to identify patterns and trends in naturalistic driving videos that may indicate the presence of anomalous or unsafe driving behaviors.

Driving activity recognition models usually capitalize

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on the richness of the visual feed provided by driver-facing camera data, to detect anomalous driving behaviors [1, 4, 23, 29]. The usual approach uses rule-based pose estimation and posture tracking, through feature detection and tracking algorithms [4, 16, 23]. Other studies have focused on gaze mapping [30], as well as the fusion of driver visual data with vehicle state characteristics [28]. This approach, whilst widely used and successful, only solves one part of the problem. Another limitation to this approach is the one-size-fits-all nature, which brings limited flexibility and adaptability to the defined rules governing the separation of normal and anomalous driving.

Given these limitations, advancements in anomalous driving behavior recognition and classification have tapped into the potential of more robust deep learning (DL) approaches [28, 29]. Researchers favor deep learning approaches because they produce better predictions and outcomes than conventional rule based and machine learning algorithms. Deep learning models are mostly utilized to enable automatic feature extraction through the training of complicated features with little external assistance to provide meaningful representations of data through deep neural networks [24].

Whilst DL approaches come with many advantages, the initial hurdle for getting them off the ground involves providing large amounts of pre-labeled data for their training [12, 17, 20]. Although this limitation is easily overcome with the availability of naturalistic driving data, the DL models are trained via sequence of event frames from video data. As such, these models expect pre-segmented video data clips in order to accurately classify the type of event taking place [5].

Video data streamed from cameras in a naturalistic driving environment are continuous and untrimmed in nature. In order to actively deploy activity recognition and classification models to such a situation, the modeling framework should have the ability to identify when anomalous driving activity is taking place whilst accurately classifying what kind of activity that is. This involves a summarized three step process of:

1. Identifying and extracting visual features from video frames
2. Defining the state of the driving behavior and observational period based on instances related to the extracted features
3. Classifying the type of driving behavior observed in the localized time sequence where the action is observed

As earlier highlighted, the more popular rule based models do a stellar job with steps 1 and 2, but are limited in

their ability to accurately classify the type of observed action (step 3), especially when there are multiple classes of observed behaviors with little variations between groups of them [29]. DL methods also have no trouble with steps 1 and 3 but usually require sequential or batch processing of the video frames [5]. Whilst it's possible to localize actions from temporal sequence by introducing techniques from rule-based algorithms, the research in this area is lacking.

The purpose of this study is to introduce a hybrid approach to continuous video activity recognition by capitalizing on the advantages of the two aforementioned approaches. The NVIDIA AI City 2023 challenge presented an opportunity to tackle this problem. In this study, we introduce DeepSegmenter, a temporal action localization algorithm which combines a DL feature detection algorithm and rule based feature tracking algorithm to first localize instances of anomalous driving behaviors (steps 1 and 2), before passing the clipped sequence of frames into a DL based activity classifier (step 3) to label the observed action as either normal driving or one of fifteen other anomalous driving behaviors.

DeepSegmenter performs incredibly well at localizing the instances of anomalous driving behaviors regardless of the length of the activity. The benefit of this approach is realized in its capacity to improve upon the current capabilities of Advanced Driver Assistance Systems (ADAS).

The rest of the paper is organized as follows. The second section discusses related research work on methods used in characterizing anomalous driving behaviour in naturalistic driving videos. The third section presents our proposed approach, while the fourth section details the experiment procedure. We then present our experimental results, which demonstrate the effectiveness of our proposed method in segmenting and classifying anomaly detection. Lastly, we discuss the implications of our findings and propose future directions for research in this field.

2. Related works

Driver action recognition has been thoroughly explored in recent years, with research into it still ongoing. By creating models to recognize or forecast driving behaviors, and implementing remedial actions for anomalous and risky driving, it will be possible to improve the safety of vehicle driving and reduce the number of driver-caused road traffic accidents. Several research publications have employed various strategies to present solutions to this idea, with the most modern methodologies relying on supervised learning strategies.

2.1. Traditional Methods

Earlier research in human activity recognition relied on empirical rule inference and quantitative statistical analysis,

such as Hidden Markov Model (HMM), Gaussian Mixture Model (GMM), Random Forest (RF), Support Vector Machine (SVM), Fuzzy Neural Network (FNN), and k-Nearest Neighbor (kNN) [33]. Using a random forest classification algorithm, Ahnagari et al. [2] identified six prevalent distracted driving behaviors with a 0.765 accuracy rate. Yao et al. [31] also developed a random forest model to identify distracted driving behavior with 0.9 accuracy. Whilst these accuracies suggest incredible strides, they are limited to binary outcomes of anomalous and normal driving, and fail in multi-classification tasks of identifying the types of anomalous driving activity observed. Traditional methods have provided us with a reasonable degree of accuracy, but their drawbacks, such as dependence on specialist experience on artificial extraction of characteristics, and inability to consider driving time sequence and correlation, can lead to driving behavior identification errors [33]. More recent advancements in the area of driver action recognition have looked into bridging this limitation by utilizing more advanced deep learning based models.

2.2. Deep learning Methods

The deep spatiotemporal features of driving behavior data can be automatically extracted using deep learning techniques like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), as well as Transformers. These techniques also incorporate feature extraction and recognition prediction into a model for end-to-end learning with high recognition accuracy. Current temporal action detection models can be classified into either single-stage detectors or two-stage detectors.

Single-Stage Detector. Single-stage detectors predict action proposals directly from video features, without the need for intermediate processes like region proposals or sliding windows [8, 15, 21, 25]. Anchor Free single-stage detector employed by Tang et al. [25] predicts the action boundaries and scores directly from the video features using an anchor free regression head and a focal loss function. Decouple-SSAD method was proposed by Rahman and Laganieri [21], this method decouples the localization and classification tasks by using parallel branches and a soft-NMS module to refine the proposals. Chen et al. [7] offers a single-stage approach that makes use of Timeception (temporal CNN), which collects multi-scale temporal information and produces action proposals and classification. Yan et al. [27] pre-trained a CNN model using unsupervised feature learning via sparse filtering, followed by fine-tuning with classification. Their system monitors the position of the driver's hands and uses extracted information to predict whether the posture is safe or unsafe. Baheti et al. [3] also used a MobileVGG network to detect and classify driver distraction. With the rise of the Transformer's attention technique that has achieved state-of-the-art results, many

recent research solutions have implemented transformers in temporal action detection [13, 15, 32].

Two-Stage Detector. A two-stage detector has two stages: one for extracting frames and one for classifying proposals/redefining temporal boundaries. Inspired by Faster-RCNN, Chao et al. [6], as well as Gao et al. [11], used a multi-scale architecture to improve receptive field alignment and exploits the temporal context of actions for proposal generation and action classification. ActionFormer, initially developed by Zhang et al. [32], was employed by Nguyen [19] to predict the temporal location of an event and do classification simultaneously, a second-stage classifier is then employed to improve prediction precision. Stragazer is also another efficient multi-scale vision transformer that learns hierarchical robust representations and then uses a sliding window for temporal localization [14]. Ding et al. [9] also proposed a Coarse-to-Fine Boundary Localization Method in which the features of the video are extracted first, and then a sliding window is used to generate coarse boundaries. Following that, the boundaries are refined to obtain the fine boundaries.

3. Approach

The overall structure of our DeepSegmenter system is illustrated in Fig 2. Our design is simple yet effective. The proposed system consists of four primary modules: Data Module, Activity Segmentation Module, Classification Module and Postprocessing Module.

3.1. Data Module

The data module is tasked with organizing and pre-processing the naturalistic driving videos. To accomplish this, the data module executes a series of preprocessing operations, including resolution normalization and pixel-value normalization. Resolution normalization entails resizing the video to a standard resolution, which ensures that the video can be analyzed uniformly across all samples as shown in Equation 1. Pixel-value normalization involves rescaling the pixel values to a standard range of 0 and 1, which eliminates differences in brightness and contrast between videos (Equation 2). By performing these preprocessing steps, the data module ensures that the collected data is in a format that subsequent modules can easily process and analyze.

$$X_{resized} = \text{resize}(X_{original}, (W, H)) \quad (1)$$

where $X_{original}$ is the original video, $X_{resized}$ is the resized video, and $\text{resize}()$ is a function that resizes the video to the specified dimensions.

$$X_{normalized} = \frac{X_{resized} - X_{min}}{X_{max} - X_{min}} \quad (2)$$

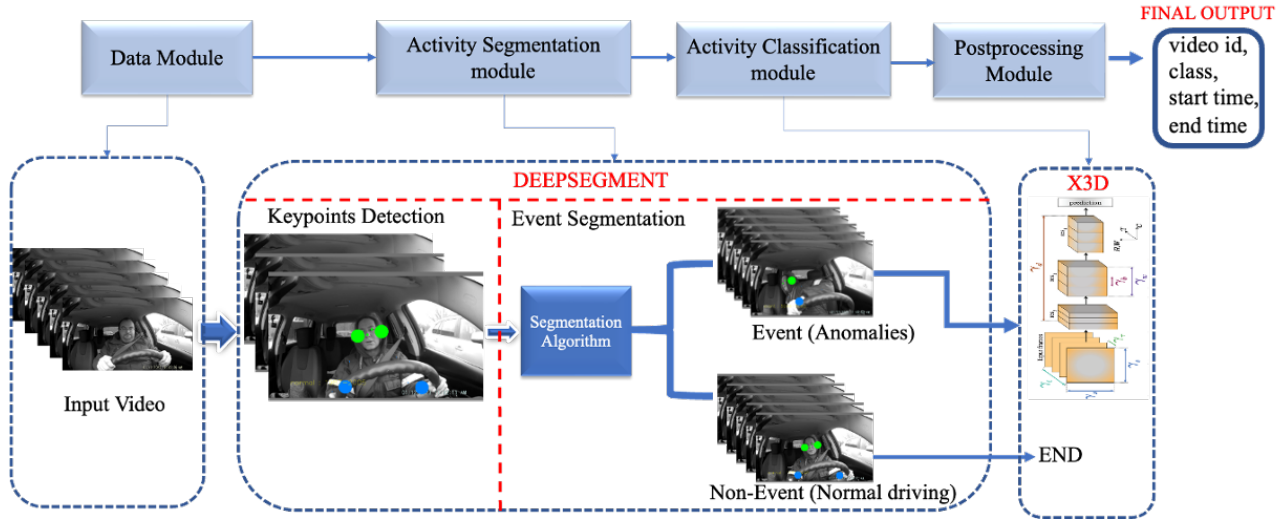


Figure 2. Overall Structure of DeepSegmenter.

where $X_{resized}$ is the resized video, X_{min} is the minimum pixel value in $X_{resized}$, X_{max} is the maximum pixel value in $X_{resized}$, and $X_{normalized}$ is the normalized video.

3.2. Activity Segmentation Module

The activity segmentation module breaks down the continuous stream of video data into discrete segments that can be analyzed and later classified. This module consists of two submodules:

Keypoint Detection. The keypoint detection submodule identifies key points in each frame of the video, such as the face and hands of the driver, which are required by the activity segmentation step. This submodule employs a pretrained yolov7 [26] keypoint detections model to detect and track the movement of these keypoints across multiple frames.

Activity Segmentation. The activity segmentation submodule uses detected key points to identify and classify driver activities as either event (anomaly) or non-event (normal driving). This submodule utilizes heuristic-based algorithm for its categorization as illustrated in Algorithm 1. Anomalies are triggered by either hand or head movements of the driver. In the case of a head anomaly, the submodule detects when the angle between the eyes and the nose surpasses a predefined threshold, if so, it classifies the frame as an anomaly, otherwise, it is considered as normal driving. Similarly, for a hand anomaly, when the angle between the hand exceeds a predefined threshold, an anomaly is triggered, else it is classified as normal driving.

3.3. Activity Classification Module

The activity classification module is in charge of classifying the segmented event into 1 of 15 different categories

Algorithm 1 Activity Segmentation

Require: θ_h, θ_{hand} (threshold angles for head and hand movements)

Ensure: classification result c for each frame

```

0: function CLASSIFYACTIVITY(frame)
1:  $keyPoints \leftarrow$  EXTRACTKEYPOINTS(frame)
2:  $headAngle \leftarrow$  CALCULATEHEADANGLE(keyPoints)
3:  $handAngle \leftarrow$  CALCULATEHANDANGLE(keyPoints)
4: if headAngle >  $\theta_h$  then
5:   return Anomaly
6: else if handAngle >  $\theta_{hand}$  then
7:   return Anomaly
8: else
9:   return Normal Driving
10: end if
10: end function
11:
11: function MAIN
12: for each frame  $f$  do
13:    $classificationResult \leftarrow$  CLASSIFYACTIVITY( $f$ )
14:   STORERESULT( $classificationResult$ )
15: end for
15: end function=0

```

of driving anomalies as shown in Table 1. This module uses a 3D CNN architecture known as X3D [10], developed for video analysis.

X3D Architecture. The X3D structure is designed to efficiently process video data using a combination of 2D and 3D convolutions. The central idea behind X3D is to expand the network in both spatial and temporal dimensions to allow for greater expressiveness while preserving efficiency.

The three components of the X3D network are the entry flow, the middle flow, and the exit flow. The entry flow initially processes incoming video frames using a series of 2D convolutional layers, followed by a 3D convolutional layer containing temporal information. The middle flow adds additional 3D convolutional layers to the network. The exit flow then reduces the output’s spatial dimensions using a combination of 2D and 3D convolutions making it easier for classification by fully connected layer as demonstrated in Fig 3.

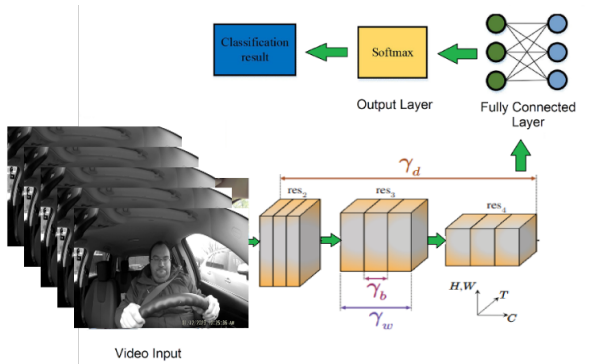


Figure 3. X3D model architecture.

X3D networks enlarge a 2D network along multiple axes, such as duration, frame rate, spatial resolution, width, bottleneck width, and depth. The application of channel-wise spatio-temporal convolutions that enable the efficient processing of video data is one of the most significant developments of X3D. These convolutions make use of shared weights across neighboring channels in a feature map, thereby reducing the number of required parameters and increasing efficiency. The ”factorized” design of X3D, in which 3D convolutions are broken down into a series of 2D convolutions, reduces the computational cost of 3D convolutions while preserving their ability to capture temporal information.

3.4. Postprocessing Module

The postprocessing module removes false positive detections, which consist primarily of events extracted for less than one second. It employs a rule-based algorithm that estimates the duration of classified events and either ignores or adds to the final submission if the duration exceeds 1 second. Finally, this module prepares the final results in the format required by the evaluation system.

4. Experiment

In this study, we assess the effectiveness of the DeepSegmenter system on the AI City Challenge dataset for Naturalistic Driver Action Recognition. Our findings reveal that

our model performs well compared to other systems when tackling this difficult task.

Data. The data set consists of 210 video clips that amount to approximately 34 hours of footage, which were taken from 35 different drivers [18,22]. Each driver performed 16 different tasks, including actions like talking on the phone, eating, and reaching back, once and in a random order. Each vehicle was equipped with three cameras that recorded from different angles in synchronization. To collect the data, each driver completed the tasks twice: once without any appearance block and once while wearing an appearance block such as sunglasses or a hat. This resulted in a total of 6 videos per each driver, with 3 videos recorded without an appearance block and 3 videos recorded with an appearance block. The summary of the activities performed by the drivers are summarized in Table 1.

Table 1. Driver Activity Summary

Activity Class type	Activity Label
1	Drinking
2	Phone Call(right)
3	Phone Call(left)
4	Eating
5	Text (Right)
6	Text (Left)
7	Reaching behind
8	Adjust control panel
9	Pick up from floor (Driver)
10	Pick up from floor (Passenger)
11	Talk to passenger at the right
12	Talk to passenger at backseat
13	yawning
14	Hand on head
15	Singing or dancing with music

Training. The experiments were carried out on an NVIDIA GTX 1080ti GPU graphics card. The activity classification model was built on the PyTorch Lightning framework. The dataset was partitioned into ratios of 0.7:0.3, corresponding to the training and validation datasets, respectively. We used the Adam optimizer with a starting learning rate of 0.001 and a weight decay of 0.001. We used the CosineAnnealingLR scheduler to adjust the learning rate during training. The model was trained for 300 epochs with a batch size of 8.

Evaluation metrics. The average activity overlap score was used as the evaluation metric in this study as shown in Equation 3. This score is determined by comparing the predicted activity with the ground-truth activity based on their overlap. The closest match will be considered as the pre-

dicted activity with the highest overlap score (os), provided that it belongs to the same class as the ground-truth activity. However, this match will only be considered if the predicted activity’s start time (ps) and end time (pe) are within a range of 10 seconds before or after the ground-truth activity’s start time (gs) and end time (ge), respectively. The overlap score is computed by finding the ratio between the time intersection and time union of the two activities.

$$os(p, g) = \frac{\max(\min(ge, pe) - \max(gs, ps), 0)}{\max(ge, pe) - \min(gs, ps)} \quad (3)$$

5. Results and Discussion

The 2023 NVIDIA AI City Challenge Track 3 test videos consists of 30 untrimmed videos from 5 different drivers at 3 different camera positions. A submission to the competition is a text file that follows the format: Video ID, Activity ID, Start time, and End time. The Video ID is a numeric identifier for the video, starting with 1 and indicating its position in the alphabetically ordered list of all Track 3, Test Set videos. The Activity ID is a numeric identifier beginning with 1 for the classified class of the anomaly. The Start and End times are integer values representing the beginning and end of the anomalous activity, respectively.

On the experimental test dataset, our proposed methodology achieved an overall overlap score of **0.5426**, ranking **8th** on the public leader board, as shown in Table 2.

Table 2. Top 10 Leader Board Ranking

Rank	Team ID	Team Name	Score
1	209	MeituanIoTVCV	0.7416
2	60	JNU_boat	0.7041
3	49	ctcAI	0.6723
4	118	RW	0.6245
5	8	Purdue Digital Twin	0.5921
6	48	BUPTMCPRL	0.5907
7	83	DiveDeeper	0.5881
8	217	INTELLILAB (Ours)	0.5426
9	152	AILAB	0.5424
10	11	AIMIZ	0.5409

6. Conclusion

This study presents a solution for Track 3 of the 2023 AI City Challenge that focuses on performing both activity segmentation and classification in a single framework called DeepSegmenter. The proposed framework is composed of four modules: Data Module, Activity Segmentation Module, Classification Module, and Postprocessing Module. According to the experimental results on the test

dataset, the proposed framework ranks 8th in the challenge with an overlap score of 0.5426. On this challenge, we demonstrated the effectiveness of our proposed framework.

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