Abstract

Temporal convolutional networks (TCNs) are a commonly used architecture for temporal video segmentation. TCNs however, tend to suffer from over-segmentation errors and require additional refinement modules to ensure smoothness and temporal coherency. In this work, we propose a novel temporal encoder-decoder to tackle the problem of sequence fragmentation. In particular, the decoder follows a coarse-to-fine structure with an implicit ensemble of multiple temporal resolutions. The ensembling produces smoother segmentations that are more accurate and better-calibrated, bypassing the need for additional refinement modules. In addition, we enhance our training with a multi-resolution feature-augmentation strategy to promote robustness to varying temporal resolutions. Finally, to support our architecture and encourage further sequence coherency, we propose an action loss that penalizes misclassifications at the video level. Experiments show that our stand-alone architecture, together with our novel feature-augmentation strategy and new loss, outperforms the state-of-the-art on three temporal video segmentation benchmarks.

1. Introduction

We tackle the problem of temporal video segmentation and classification for untrimmed videos of complex activities. A complex activity is usually goal-oriented, e.g. ‘Frying eggs’ and composed of multiple steps or sub-actions in some sequence, e.g. ‘Pour Oil’, ‘Crack Egg’, ... ‘Put to Plate’ over time. The standard framework for temporal segmentation is MS-TCN [32, 9]. MS-TCN uses temporal convolutions with progressively larger dilations to maintain a constant temporal resolution throughout the feedforward architecture. Multiple works further augment the MS-TCN model [51, 46] with additional model training or post-processing smoothing.

We posit that maintaining a constant temporal resolution is suboptimal for handling video sequences. In this work, we propose an encoder-decoder instead: the encoder reduces the temporal resolution to some bottleneck feature before a symmetric decoder gradually recovers the sequence back to the original temporal resolution. Such a shrink-then-stretch strategy is in line with many other works in vision for image segmentation [38, 14], depth and flow estimation [44] and landmark detection [34, 52].

In fact, encoder-decoders have also been used for video sequence understanding in the past [29, 31, 6], though their performance is not strong. We believe that possible causes include the simple bottleneck and decoder design. Furthermore, the decoder must be carefully designed for action segmentation because of the significant variation in the sub-action lengths.

To handle different sub-action lengths, we propose a novel “coarse-to-fine ensemble” of decoder output layers. Our ensemble is not only more accurate, but also has a smoothing effect and yields more accurately calibrated sequences. Incorporation of “coarse-to-fine ensemble” of decoder outputs is a key novelty of our work in comparison to previous temporal Encoder-Decoder architectures [29, 31, 6]. To support our proposed architecture, we incorporate the following two simple yet effective novelties.

Video-level loss: Firstly, we propose a video-level “Action Loss”. Currently, temporal convolutional frameworks for videos are all trained with frame-level losses; however, these do not adequately penalize sequence-level misclassification. To augment the frame-level losses, we introduce a novel video level “Action Loss” to penalize sub-actions not associated with the complex activity label. Such a loss is highly advantageous in mitigating the effects of over-segmentation and prevent fragmented sequence segmentation.

Multi-resolution feature augmentation: Although augmentations are quite common in deep learning, as per our knowledge, none of the previous work considers data augmentation for sequence segmentation, likely due to the following reasons. A direct translation of augmentation techniques from images would require perturbations to the video frames [16, 48]. This would not only be computa-
tionally expensive but suffer domain gap problems since the
standard is to use pre-computed features from pre-trained
networks. As an alternative, we consider augmentation at a
feature level [8] specifically for video sequences. Specific-
ally, we propose “multi-resolution feature-augmentation”
strategy, which augments video sequences by considering
features of different sampling rates. This adds robustness
to the model and allows the network to learn to handle sub-
sampled resolutions of video. Previous works [9] found that
using lower frame-rates drops the accuracy, motivating the
need for a full (temporal) resolution framework which is
computationally expensive. We can derive higher accuracy
with frame rates much lower than that of the original video
through our augmentation strategy.

Uncertainty quantification in Action Segmentation: Due to the direct application of video action segmentation in real-life human activities, models with over-confidently
wrong predictions can lead to disastrous consequences.
Thus, it is highly crucial for the models to have good pre-
diction uncertainty. Traditional neural networks are known
to be over-confident in their predictions [15]. Among all the
available solutions that combat over-confidence, probability
ensembles are one of the most effective [28, 30] especially
in the presence of abundant training set [36]. We thus high-
light the calibration performance of our proposed method in
this work.

To summarize, our main contributions are

1) We design an novel temporal Encoder-Decoder ar-
chitecture C2F-TCN for temporal segmentation. This uti-
ifies the coarse-to-fine resolutions of decoder outputs to
give more calibrated, less fragmented, and accurate outputs.

2) We propose a multi-resolution temporal feature-level
augmentation strategy that is computationally more efficient
and gives a significant improvement in accuracy.

3) We propose an “Action Loss” which penalizes mis-
classifications at the video level and enhances our frame-
level predictions. This global video-level loss serves as an
auxiliary loss that complements the frame-level loss without
any additional network structure.

4) We adapt our temporal segmentation model C2F-
TCN to recognize the minutes-long video and achieves
SOTA performance.

2. Related Work

Action Recognition. The task of recognition requires
classifying the video as whole whereas task of segmenta-
tion requires classifying each frame of the video. For short
trimmed videos (2 – 10 sec) architectures for action recogni-
tion include two-stream 2D CNNs [12, 40], CNNs together
with LSTMs [7, 45], 3D CNNs [24, 43]. More recent archi-
tectures include a two-stream 3D-CNN (I3D) [2], non-local
blocks [50], SlowFast network [11] and the Temporal Shift
Module [33].

For longer, untrimmed videos, the computational cost of
directly training such deep 3D convolutional architectures is
computationally very expensive and data deficit. Most ap-
proaches resort to extracting snippet-level features based on
the previously-mentioned architectures and add additional
dedicated sequence-level processing for either recognition
or segmentation. Examples include TCN networks [6, 29,
31, 32, 9], RNNs [27, 41, 35], graphs [21], dedicated archi-
tectures like the temporal inception network [20] or atten-
tion modelling [22, 39]. Our work falls into this category
where we model temporal relationships on top of snippet
level I3D features.

For only long video recognition, some use temporal
convolutions [20], attention [22, 21] or graph modelling
[21]; others use aggregating models like ActionVLAD [13]
and some generating framework for recognition [25]. Dif-
ferent from these we adapt our segmentation model to be
used for temporal action recognition task as it captures both
global relationships and local fine-grained information for
recognizing the video action.

Action Segmentation. Initially, models for temporal
video segmentation were based on statistical length mod-
elling [37], RNNs [35, 41, 35], and RNNs combined with
Hidden Markov models [27]. The recursive nature of RNNs
make them slow and difficult to train, especially for long
sequences. More recent architectures treat the entire video
sequence as a whole and model coarse units within the se-
quency either via non-local attention [39] or graph conv-
olutional networks [19]. However, these approaches cannot
account for the fine-grained temporal changes in videos, re-
quired for segmentation.

Several works have shown the effectiveness of tempo-
ral convolutional networks (TCN) [6, 29, 31, 9, 32]. MS-
TCN [9, 32] stacks a temporal convolutions with dilat-
tion, without max-pool to capture the relationships in long
videos. Encoder-decoder TCN’s [6, 29, 31] uses gradual
reduce and expanded resolution convolutions. In line with
Encoder-Decoder TCN’s, we design our model architecture
C2F-TCN. However, we are first to explore the coarse-to-
fine decoder layer’s ensemble. Segmentation with TCN still
suffers from over-fragmentation errors, which are handled with
refinement layers [9, 32], LSTMs on top of refinement
layers [46], or separate boundary detection model with post-
processing smoothing [51, 23]. Different from these, we
handle over-fragmentation with our implicit model’s com-
ponents ensembling which does not require any additional
network structure.

3. Methodology

The aim of video action segmentation is to assign a la-
bel to each frames of a video. More formally, it deals with
video \( V \in \mathbb{R}^{T \times H \times W} \), where for each temporal location
\( t \in \mathcal{T} := \{1, ..., T\} \), frame \( V_t \in \mathbb{R}^{H \times W} \) is an image
of dimension $H \times W$. With a pre-defined set of $C$ action classes $A := \{1, ..., C\}$, the task of action segmentation is to find a mapping $\hat{y} : T \rightarrow A$ that maps each frame $V_t$ to an action label $\hat{y}_t \in A$. Our method is supervised; the model $M$ takes a video $V$ as input and produces predictions $M(V) = \{p_t\}_{t=1}^T$ where each $p_t \in \mathbb{R}^C$ is a probability vector of dimension $C$. The predicted label for each $t$ is then obtained by $\hat{y}_t = \text{arg max}_t p_t$ and the corresponding probability by $\hat{p}_t = \text{max}_t p_t$, with the max and arg max over all possible actions in $A$. To overcome the computational challenge of training an end-to-end model, the standard practice is to use pre-trained frame level features. We work with such pre-trained feature representation of every frame $t$ denoted by $f_t \in \mathbb{R}^d$. Furthermore, instead of using the features at full temporal length $T$, we down-sample $f$ to obtain coarser features $f^{\text{in}}$ of temporal dimension $T^{\text{in}}$, which we use as input to our model. We discuss the details of our down-sampling strategy in subsection 3.3. However, it should be noted that for each video during inference, we always up-sample our predictions $\{\hat{y}_t : t \leq T^{\text{in}}\}$ to the original temporal length $T$, in order to compare with original ground truth $\{y_t\}_{t=1}^T$.

3.1. Model Architecture:

Our model’s architecture can be separated into three components, i.e. $M := (\Phi : \Gamma : \Psi)$, consisting of the encoder $\Phi$, bottleneck $\Gamma$ and decoder $\Psi$. Below we discuss each component of the architecture in more details.

**Encoder network $\Phi$:** The input to the encoder network is the down-sampled frame-level features $f^{\text{in}} \in \mathbb{R}^{T^{\text{in}} \times d}$, where $d$ denotes channel dimension of input feature. The encoder network consists of a 1-D convolutional block $\Phi^{(0)}$ and six sequential encoder blocks $\{\Phi^{(i)} : i \leq 6\}$. At the beginning, $\Phi^{(0)}$ projects $f^{\text{in}}$ to feature of dimension $T^{\text{in}} \times d_0$; for $i \geq 1$, the outputs of $\Phi^{(i)}$ are $\mathbb{R}^{T_i \times d_i}$, where $T_i$ and $d_i$ are the temporal and feature dimensions of each block $i$ respectively. Each encoder consists of a convolutional block and a max-pooling unit that halves its input’s temporal dimension.

**Bottleneck network $\Gamma$:** To ensure flexibility in the input video resolution and to facilitate temporal augmentations, we introduce a pyramid pooling [17] along the temporal dimension. Pyramid pooling has been used in the past to handle multi-resolution inputs for segmentation, detection, and recognition task in both images and videos [18, 49, 3, 4, 14, 53].

The input to the bottleneck $\Gamma$ is the output $f^{\text{en}}$ of the last encoder layer $\Phi^{(6)}$. We create four redundant representations of $f^{\text{en}}$ of varying temporal resolutions via four parallel max-pooling units of varying kernel sizes $\{w_i^\gamma : i \leq 4\}$. The max-pooling reduces $f^{\text{en}}$ to a smaller temporal dimension $\left[\frac{T^{\text{en}}}{w_i^\gamma}\right]$; each feature is then collapsed by a shared 1D convolution of kernel size 1 to a single latent dimension while the temporal dimension is kept fixed. These four redundant representations are then up-sampled with linear interpolation back to the original temporal dimension $T^{\text{en}}$. Along with the features $f^{\text{en}}$, the four features of dimension $T^{\text{en}} \times 1$ are concatenated along latent dimension to produce a bottleneck output of $\mathbb{R}^{T^{\text{en}} \times (4+d^{\text{en}})}$. Owing to the shared nature of the single 1-D convolution unit, the bottleneck network contains marginal parameters.

**Decoder network $\Psi$:** Structurally, the decoder network is symmetric to the encoder; it has six decoder layers $\{\Psi^{(i)} : i \leq 6\}$, each containing an up-sampling unit and the same convolution block as the encoder (see Fig. 1). For each $i \geq 1$, the up-sampling unit linearly interpolates or stretches inputs to an output of twice the temporal length. This is then concatenated with $\Phi^{(6-i)}$, i.e. the output of the $(6-i)^{th}$ encoder block via a skip connection. The output of the $i^{th}$ decoder block thus has temporal dimension same as $T_{6-i}$ and latent dimension 128. The skip-connection ensures that both global information (from the decoder) and

![Figure 1. Our segmentation architecture: Depiction of the architecture of our model ($\Phi : \Gamma : \Psi$). We utilize our multi-resolution features to produce Coarse-to-fine Ensemble predictions.](image-url)
local information (from the encoder). The last decoder layer \( \Psi^{(i)} \), with a skip connection from \( \Phi^{(i)} \) generates output of \( \mathbb{R}^{T^{in} \times 128} \).

3.2. Coarse-to-Fine Ensemble (C2F Ensemble):

Rather than taking the last decoder layer as the output, we propose to ensemble the results from several decoder layers. For each \( i \geq 1 \), we project the output of the \( i^{th} \) decoder block \( \Psi^{(i)} \) to \( C \) dimensions, i.e. the number of actions and follow with a softmax operation to produce probability vectors \( \mathbf{p}^{(i)} \) which get up-sampled with linear interpolation to the input temporal dimension \( T^{in} \) and ensembled. Thus, for any \( 1 \leq t \leq T^{in} \), the ensembled prediction \( \mathbf{p}^{ens} = \mathbf{R}^{C} \) takes the form:

\[
\mathbf{p}^{ens}_t = \sum_i \alpha_i \cdot \text{Up}[\mathbf{p}^{(i)}, t], \quad \sum_i \alpha_i = 1, \quad \alpha_i > 0
\]

where \( \alpha_i \) are the ensemble weights of the \( i^{th} \) decoder layer, and \( \text{Up}(\cdot, t) \) is a function that returns the interpolated vector at time \( t \). The sum in Eq. 1 is performed action class-wise, with the final predicted action label as

\[
\hat{y}_t = \arg \max_{k \in \mathcal{A}} \mathbf{p}^{ens}_t.
\]

The ensembled predictions \( \mathbf{p}^{ens} \) is used during both training and inference; we refer to it as a coarse-to-fine ensemble (C2F ensemble). Our rationale for using an ensemble is twofold. First, the earlier decoder layers are less susceptible to fragmentation errors by being coarser in their temporal resolution. Incorporating these outputs helps to mitigate over-segmentation. Such multi-resolution ensemble is made possible due to the shrink-then-stretch policy of encoder-decoder architecture. In contrast, architectures such as MS-TCN keep the temporal dimension unchanged, requiring additional refinement stages to correct over-segmentation. Secondly, standard network outputs tend to be over-confident in their predictions [15] which we discuss later in section 4.5. Probability ensembles are an effective way [28, 30] to reduce overconfidence, especially with sufficient training data [36].

3.3. Multi-Resolution Feature Augmentation:

As discussed earlier, we down-sample the pre-trained feature representations \( \mathbf{f} \) to obtain the input feature vector \( \mathbf{f}^{in} \in \mathbb{R}^{d} \) and ground truth \( \hat{y}^{in} \in \mathcal{A} \). Instead of standard subsampling, we use max-pooling, which has been found to be beneficial for representing video segments in [39]. Instead of max-pooling with a fixed window size, we consider multiple resolution of the features by varying the window. At time \( t \), for some temporal window \( w > 0 \), we max-pool along the temporal dimension within a temporal window of \( w \):

\[
f^{w}_t = \max_{\tau \in [wt, wt + w]} \mathbf{f}_\tau,
\]

while taking the ground truth action that is most frequent in the window \([wt, wt + w]\) as the corresponding label

\[
y^{w}_t = \arg \max_{k \in \mathcal{A}} \sum_{\tau = wt}^{wt+w} \mathbb{I}[y_{\tau} = k]
\]

The pooled features \( \mathbf{f}^{w} := \{\mathbf{f}^{w}_t\} \) and ground truth \( y^{w} := \{y^{w}_t\} \) both have a temporal dimension of \( T^{w} := \left\lfloor \frac{T}{w} \right\rfloor \). By using a varying set of windows \( \mathcal{W} \subset \mathbb{N} \), a corresponding set of feature-ground truth pair \( \mathcal{D}_{aug} := \{\{\mathbf{f}^{w}, y^{w}\} : w \in \mathcal{W}\} \) can thus be obtained.

By equipping \( \mathcal{W} \), and by extension \( \mathcal{D}_{aug} \), with a probability distribution \( \pi \), we formulate a stochastic augmentation strategy. We work with a specific class of probability distribution \( \Pi := \{\pi(\cdot ; w_0) : w_0 \in \mathbb{N}\} \) parameterized by a “base window” \( w_0 \). For a base window, we define an upper and lower bound \( w_{max} := 2w_0 \) and \( w_{min} := \left\lfloor \frac{w_0}{2} \right\rfloor \), and \( r := w_{max} - w_{min} \). Then we define distribution \( \pi \) as

\[
\pi(w; w_0) = \left\{ \begin{array}{ll}
\pi_0 & : w = w_0 \\
(1 - \pi_0)/r & : \text{otherwise}
\end{array} \right.
\]

where \( 0 \leq \pi_0 \leq 1 \) is the probability of sampling the base window. We assign zero probability to any window size outside the bounds. In our experiments we found \( \pi_0 = \frac{1}{2} \) to be most effective.

Apart from the obvious advantage of the increased effective size of the training data, this augmentation strategy encourages model robustness with respect to a wide range of temporal resolutions. At test time, we can also combine predictions for different temporal windows.

Before combining, all the predictions are interpolated to the original temporal dimension \( T \) of the test example. We compute the expectation of the prediction probabilities under the distribution \( \pi \). Formally, for any \( t \leq T \) and \( k \in \mathcal{A} \) our final predictive likelihood is

\[
P(\hat{y}_t = k) = \mathbb{E}_{w \sim \pi} \left[ P(\hat{y}_t = k | \mathbf{f}^{w}) \right]
\]

where \( P(\hat{y}_t = k | \mathbf{f}^{w}) \) is the conditional probability of the frame \( t \) being labelled with action class \( k \) given input features \( \mathbf{f}^{w} \) max-pooled with window \( w \).

3.4. Training Losses:

During our training procedure, we make use of three different losses. The first, \( \mathcal{L}_{CE} \), is the standard frame-level cross-entropy for action classification:

\[
\mathcal{L}_{CE} = \frac{1}{T} \sum_{t} \sum_{k \in \mathcal{A}} \mathbb{I}[y_t = k] \log P(\hat{y}_t = k)
\]

where \( y_t, \hat{y}_t \) are the ground truth and the predicted label respectively. The second is the transition loss used in [9, 32]
This loss ensures that we maximize the ability assigned to class \( k \) for any action \( k \) present in video \( V \). Let \( \delta_k^{\text{pres}} \) be the indicator whether the action \( k \) is present in video \( V \) and \( \pi_k^{\text{pres}} := \max_i \mathbb{P}[\hat{y}_i = k] \) be the maximum action probability assigned to class \( k \) across the whole video. We define our Video-level Action Loss as

\[
L_{\text{AL}} = - \sum_{k \in \mathcal{A}} \delta_k^{\text{pres}} \cdot \log \pi_k^{\text{pres}} - \sum_{k \in \mathcal{A}} \left( 1 - \delta_k^{\text{pres}} \right) \cdot \log (1 - \pi_k^{\text{pres}}). \tag{8}
\]

This loss ensures that we maximize the \( \pi_k^{\text{pres}} \) for all actions present in a video. More importantly, though, it allows us to minimize \( \pi_k^{\text{pres}} \) for any action \( k \) not present in the entire video, thereby limiting misclassifications by actions not related to the complex activity.

The three loss terms can be summed into a joint loss \( L \):

\[
L = L_{\text{AL}} + L_{\text{CE}} + \lambda_{\text{TR}} L_{\text{TR}} \tag{9}
\]

where \( \lambda_{\text{TR}} = 0.15 \) as suggested by [32, 9].

### 3.5. Complex Activity Recognition:

Our framework can be adopted easily from video segmentation to classify the overall complex activity. We use the encoder-decoder architecture as described in Section 3.1 to obtain output \( p_t \) and then max-pool over time before applying a two-layer MLP followed by a softmax:

\[
p_V = \text{MLP} \left[ \max_t (\log p_t) \right]. \tag{10}
\]

where \( p_V \in \mathbb{R}^K \) is the probability vector for the \( K \) complex activities. Intuitively, max-pooling along the temporal dimension retains the important information over time and is invariant to permutation of action orders within the video. Similar to other works [20, 22], we do not use any frame wise sub-action labels. Instead, we train our segmentation network separately with the following loss

\[
L_V = - \sum_{k=1}^{K} \mathbb{I}[y_V = k] \log \mathbb{P}[\hat{y}_V = k]. \tag{11}
\]

where \( y_V, \hat{y}_V \) are the ground truth and the predicted complex activity of video sequence \( V \).

### 3.6. Calibration:

The calibration of a prediction is a measurement of over/under-confidence. Earlier we defined maximum probability prediction of a frame \( t \) to be \( \hat{p}_t := \max p_t \). In calibration literature, \( \hat{p}_t \in [0,1] \) is termed as confidence of the prediction \( \hat{y}_t = \arg \max p_t \). The accuracy of a confidence value \( p \in [0,1] \), denoted by \( \text{Acc}(p) \) is the action classification accuracy of frames with maximum probability prediction \( \hat{p}_t \) equal to \( p \). Ideally, one would like the Acc
to be high for high values of confidence and vice-versa. A model is calibrated if \( \text{Acc}(p) = p, \forall p \in [0, 1] \) and it is called over-confident (or under-confident) if \( \text{Acc}(p) \leq p \) (or \( \text{Acc}(p) > p \)). The above definition of Acc is often made practical by calculating the accuracy for a range of confidence values \( P \subset [0, 1] \), rather than one particular value \( p \). Thus the modified definition becomes 

\[
\text{Acc}(P) := \frac{\sum_i I[\hat{y}_i = y_i \cdot I[\hat{t}_i \in P]]}{\sum_i I[\hat{t}_i \in P]}
\]

For \( P = [0, 1] \), the definition of accuracy reduces to the standard classification accuracy. We use this notion of confidence and accuracy to later measure the calibration performance of temporal segmentation in sub-section 4.5.

### 4. Experiments

#### 4.1. Datasets, Evaluation, and Implementation:

We evaluate on three standard action segmentation benchmarks: Breakfast Actions [25], 50Salads [42] and GTEA [10]. Breakfast Actions is a third-person view dataset of 1.7k videos of 52 subjects performing ten high-level tasks for making breakfast. On average, the videos are 2.3 minutes long with 6 subactions (a total of 48 possible actions). 50Salads has top-view videos of 25 people preparing 2 mixed salads each, totally 50 videos with 19 different sub-actions. The videos have average length of 6.4 minutes and an average of 20 actions. GTEA captures 28 egocentric videos of 7 complex activities with 11 sub-actions. The average duration of videos is 1.5 minutes with 20 sub-action instances.

For evaluation, we report Mean-over-frames (MoF), segment-wise edit distance (Edit) and F1-scores with IoU thresholds of 0.10, 0.25 and 0.50 (F1@\( \{10, 25, 50\} \)). For all three datasets, we use features pre-extracted from an I3D model [2] pre-trained on Kinetics, and follow the k-fold cross-validation averaging to report our final results. Here \( k = \{4, 5, 4\} \) for Breakfast, 50Salads and GTEA respectively. The evaluation metrics and features follow the convention of other recent temporal video segmentation methods [39, 32, 51, 23].

**Implementation Details** In our experiments we train using an Adam optimizer for 600 epochs, with learning rates of \( \{10^{-4}, 3 \times 10^{-4}, 5 \times 10^{-4}\} \), weight decay of \( \{3 \times 10^{-3}, 10^{-3}, 3 \times 10^{-4}\} \), batch size of \( \{100, 25, 11\} \) and a base window for sampling \( w_0 \) of \( \{10, 20, 4\} \) for Breakfast, 50Salads and GTEA respectively. While choosing the base window we ensure it is small enough not to drop any sub-action or fragments. The ensemble weights used were \( \alpha_i = \frac{1}{i}, \forall i \geq 3 \) for all three datasets. We find for \( i \leq 2 \), the results of the ensemble degrade due to very coarse temporal resolutions.

#### 4.2. Ablation Studies & Model Analysis:

In Table 1 we perform a component-wise analysis of our core contributions. In the first row, we start with the base model \( M := (\Phi : \Gamma : \Psi) \) with the probability outputs \( \text{p}^{(6)} \) from the last decoder layer. This base model already outperforms other temporal encoder-decoder architectures such as ED-TCN [29] and Residual Deformable ED-TCN [31] (see Table 2). The gradual addition of each component which we detail below, shows a steady improvement of results.

**Impact of Coarse-to-Fine Ensemble:** Adding the decoder ensemble to the base model gives a significant improvement in Edit and F1 scores on all three datasets. The Edit score improves by +5.7 %, +7.5 %, +2.7 % on Breakfast, 50Salads and GTEA; the extent of improvement directly aligns with the average length of the videos. The improvement over the base model in F1@50 is also a significant +5.7 %, +3.9 %, +4.4 %; this demonstrates the usefulness of our decoder ensembling. With only the ensembling, we can exceed the performance of MS-TCN++ (see Table 2 row 5) in all the scores on Breakfast Actions dataset.

**Analysis of Coarse-to-Fine Ensemble:** Figure 2 shows a qualitative and quantitative analysis of the ensemble compared to the individual decoder layers \( \Psi^{(i)} \) which form the ensemble. The left plot shows our model’s segmentation output on a sample video where each color denotes a sub-action. The output from the last decoder layer \( \Psi^{(6)} \) becomes over-fragmented (blue patch), which does not corrupt the ensembled result. Plotting the MoF, Edit, and F1@50 scores (see Fig. 2 right), we find that the fourth decoder layer \( \Psi^{(4)} \) has the strongest individual performance and that these results erode with further decoding. However, incorporating all the layers in the C2F ensemble yields a significant boost, especially in Edit distance, which is the measure most affected by fragmentation.

**Number of Layers used in C2F Ensemble:** We mention that we use ensemble weights with \( \alpha_i = \frac{1}{i}, \forall i \geq 3 \) and \( \alpha_i = 0, \forall i \leq 2 \). This is found using experimental validation shown in Table 3. The first column shows the unnormalized weights. Here we perform an ablation study in Breakfast dataset on how many layers of Decoder’s output are useful for ensembling. We use our final proposed model with C2F Ensemble, Action Loss, Train, and Test Augmentation and only modify the weights \( \alpha_i \) in the ensemble to perform the ablation. We see that we get the maximum of Edit, MoF and F1 scores at Last four layers, i.e. when \( \alpha_i = 1/4, \forall i \geq 3 \) and \( \alpha_i = 0, i \leq 2 \).

**Impact of Multi-Resolution Feature-Augmentation Strategy:** Table 1 row 3 shows that adding feature augmentation during training provides a boost in all scores across all datasets. The maximum improvement of scores with train augmentation strategy is seen in Breakfast Action dataset with +3.2% MoF and +3.4% Edit scores. In row 5, we observe additional improvement with test-time aug-
Table 1. Ablation study on each component of our proposal. We gradually add (+) each part of our proposed method to show its effectiveness. To highlight the fact that temporal pyramid pooling is most effective when inputs are of varying resolution, we show its ablation as removal (–) only after we add train and test augmentation to our method stack.

| Method                  | Breakfast | 50Salads | GTEA     |
|-------------------------|-----------|----------|----------|
| Base Model \( \Phi, \Psi \) | \( F1@\{10, 25, 50\} \) | \( \text{Edit MoF} \) | \( F1@\{10, 25, 50\} \) | \( \text{Edit MoF} \) | \( F1@\{10, 25, 50\} \) | \( \text{Edit MoF} \) |
| (+) C2F Ensemble        | 56.6 52.5 43.4 57.4 65.8 | 67.5 64.3 53.9 59.1 77.5 | 87.1 82.6 69.3 81.4 77.3 |
| (+) Train Augment       | 64.5 60.4 49.1 63.1 70.2 | 72.3 68.8 57.8 66.6 78.4 | 88.1 86.8 73.7 84.1 78.5 |
| (+) Action Loss         | 69.4 65.9 55.1 66.5 73.4 | 75.8 73.1 62.3 68.8 79.4 | 90.1 87.8 74.9 86.7 79.5 |
| (+) Test Aug. \( \text{(final)} \) | 70.1 66.6 56.2 68.2 73.5 | 76.6 73.0 62.5 69.2 80.1 | \textbf{90.5} 88.5 77.1 \textbf{87.3} 80.3 |
| (–) TPP layer \( \Gamma \) | 72.2 68.7 57.6 69.6 76.0 | \textbf{84.3} 81.8 72.6 76.4 84.9 | 90.3 \textbf{88.8} 77.7 86.4 \textbf{80.8} |

Table 2. Comparison with recent related work. Our proposed model exceeds in most of the scores across all datasets.

| \( \{\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6\} \) | Breakfast | 50Salads | GTEA     |
|-------------------------------------------------------------|-----------|----------|----------|
| \{0, 0, 0, 0, 0, 0\} | 65.7 62.2 52.7 65.3 75.8 | 68.0 63.9 52.6 52.6 64.7 | 72.2 69.3 56.0 64.0 |
| \{0, 0, 0, 1, 1\}  | 67.0 63.2 52.9 65.0 75.5 | 72.9 68.5 57.2 66.0 68.1 | 79.2 74.4 62.7 74.1 70.1 |
| \{0, 0, 1, 1, 1\}  | 67.6 64.2 54.6 66.9 75.3 | 76.3 74.0 64.5 67.9 80.7 | 85.8 83.4 69.8 79.0 76.3 |
| \{0, 1, 1, 1, 1\}  | 72.2 \textbf{68.7} 57.6 69.6 76.0 | 75.4 72.8 63.9 67.5 82.6 | 87.8 86.2 74.4 82.6 78.9 |
| \{1, 1, 1, 1, 1\}  | 71.4 67.8 57.1 68.8 74.8 | 78.0 76.2 67.0 71.4 80.7 | 89.1 87.5 72.8 83.5 76.7 |
| \{1, 1, 1, 1, 1\}  | 70.6 66.5 55.6 67.6 74.4 | 82.3 81.3 \textbf{74.0} 74.3 84.4 | 88.5 87.1 77.3 84.4 79.8 |

Table 3. Ablation study on number of layers used in C2F Ensemble on Breakfast dataset.

4.3. Comparison with SOTA:

Table 2 compares our performance against recent and related SOTA segmentation approaches. All the listed works use the same 3D features and evaluation splits. There are few other works on temporal segmentation which are not directly comparable [23, 5]. SSTDA [5] uses self-supervised task’s adapted features to train the segmentation architecture, Alleviating-Over-segmentation [23] uses features extracted from fully-trained MS-TCN[9] architecture to train segmentation architecture.

Our model outperforms the SOTA scores by +5.6%, +2.6%, +3.2 % on MoF, \( F1@0 \) and \( F1@25 \) scores on Breakfast, the largest of three datasets. Our Edit score is slightly lower than GateR[46]. However, GateR’s MoF is -8.3 % less than ours. For the smaller 50Salads, we outperform the SOTA scores by +2.1 %, +2.0 % on Edit and \( F1@0 \). For \( F1@0 \), we are slightly lower than BCN[51], but for all other measures and datasets, BCN is worse. On GTEA, we outperform SOTA scores on all metrics with +1.0%, 2.0%, 1.7% on MoF, Edit, and \( F1@25 \) scores. We conclude from these strong evaluation scores that our method can generalize to different types of videos and datasets.

Impact of Video Length: For a closer look, we split the videos into three length categories and tally our results. In comparison, we train an MS-TCN++[32] model, which achieves comparable or higher scores than reported in the original paper in all metrics. In the Table 5 we show the...
MoF % for various video lengths. We observe that after training augmentation (row 3), our performance improves regardless of the videos’ length. For the longer videos (≥ 2.5 mins), our final proposal achieves +5.7% MoF over the MS-TCN++ model.

4.4. Evaluation of Complex Activity Recognition:

In Table 4 we show our results on Action Recognition task. We compare against several methods with varying architectures [13, 21, 20, 22] ranging from graphs to multi-scale self-attention dedicated in their design for long-video recognition. Unlike these works, we adapt a segmentation architecture but find that we can still outperform these other works. For a fair comparison, we use the same splits provided by [21, 20, 22], which has {1357 : 335} videos for training and evaluation. We use features from 13D pre-trained on Kinetics [2] dataset, and it is not fine-tuned for the Breakfast Action dataset. Our base model is +15.4 % above other methods without fine-tuned features and competitive with other methods that do use fine-tuned features. Adding the subsequent components steadily improves our results surpassing SOTA that uses fine-tuned 13D features by +5% even though our features are not fine-tuned.

4.5. Uncertainty Quantification:

As motivated in section 1 it is crucial to evaluate models dealing with videos based on uncertainty quantification. Hence, we evaluate our model by comparing its calibration performance of predictions from our final proposal (with test time augment), C2F ensemble, and our final prediction with the trained MS-TCN++ model of 4.3. We follow the notations defined in sub-section 3.6. To make the calibration plot, we partition the unit interval [0, 1] into N equal length bins \( P_n := \left( \frac{n}{N}, \frac{n+1}{N} \right) \), and compute \( \text{Acc}_n := \text{Acc}(P_n) \). We then obtain the 2-D curve \( \{(\frac{n+1}{2N}, \text{Acc}_n) : 1 \leq n \leq N\} \) in which the x-axis denotes confidence (mid-point of interval \( P_m \)) and y-axis denotes its corresponding accuracy. For better visualization, we plot the difference between accuracy and confidence in the y-axis. In the first two plots of figure 3 we compare the calibration performance of predictions from our final proposed stack (with train and test augment), C2F ensemble prediction, MSTCN++, and prediction from different decoder layers. Our final proposal gives the most calibrated result. In addition, our C2F ensemble is more calibrated than MSTCN++. For the last plot, we calculate the Shannon Entropy of probability predictions for incorrect segmentation. Higher entropy indicates more uncertainty in prediction. We plot the density of the calculated entropy for MSTCN++ and our C2F ensemble. Our ensemble predictions are more uncertain when the model is wrong.

| Method           | Feature | Not Fine Tuned | Fine Tuned |
|------------------|---------|----------------|------------|
| ActionVLAD [13]  | I3D     | 65.5           | 82.7       |
| VideoGraph [21]  | I3D     | 69.5           | -          |
| Timeception [20] | I3D     | 71.3           | 86.9       |
| Generative [26]  | FV [47] | 73.3           | -          |
| PIC [22]         | I3D     | -              | 89.9       |
| Actor-Focus [1]  | I3D     | 72.0           | 89.9       |
| Ours Base Model  | I3D     | 88.7           | -          |
| (+) C2F Ensemble | I3D     | 90.7           | -          |
| (+) Train Aug.   | I3D     | 92.1           | -          |
| (+) Test Aug.    | I3D     | 94.9           | -          |

Table 4. Complex Activity Recognition: we outperform previous SOTA without using fine-tuned features.
Our proposed setup

Figure 4. Computational resources: In the first two figure, we compare the average time (in seconds) per example used during training on Breakfast dataset. In addition to comparing MSTCN++ with our proposed method (denoted as our proposed setup), we also compare the resource used when our proposed method is run with full resolution inputs (denoted by our model (full resolution)) as done in MSTCN++. All the graphs terminate when the batch size could not be fit into a single GPU. For better visualization, some graphs use a logarithmic scale on the x-axis (batch size). Our method takes considerably less computing time and memory.

Table 5. MoF for varying lengths of videos from Breakfast Dataset.

| Duration       | ≤ 1 min | > 1 and ≤ 2.5 | > 2.5 min |
|----------------|---------|---------------|-----------|
| No. of Videos  | 534     | 584           | 594       |
| MSTCN++[32]    | 68.7    | 70.5          | 70.2      |
| Ours C2F Ensemble | 68.9    | 69.8          | 69.7      |
| (+) Train-Aug  | 72.9    | 72.9          | 72.7      |
| (+) Test-Aug (final) | 73.0    | 73.3          | 75.9      |

4.6. Computational efficiency:

In this section, we discuss the computational benefits in terms of memory-usage and compute-time of our proposed method compared to MSTCN++[32].

The computation gains stem from two main reasons:

1. Shrink-then-stretch of temporal resolution compared to maintaining the same temporal resolution architecture of MS-TCN/MS-TCN++ [9, 32].

2. Feature sub-sampling obtained from temporal pooling as described in Multi-Resolution Feature Augmentation subsection 3.3 compared to using full resolution features as motivated in [9, 32].

We report two metrics: (1) Average Training Compute Time per video, (2) Maximum GPU Memory usage during training. To report the compute time, we exclude the time taken for data preparation and transfer time between devices, thus only capturing the time for the forward and backward pass during training. We report all our metrics based on a single Nvidia GeForce RTX 2080 Ti GPU with 10.76 Gb of memory. We compare our architecture to the base model MS-TCN++ [32]. We further note that other methods in the SOTA comparison, like BCN [51] and Gat-edR [46], all use MS-TCN++ as their base architecture, with additional model components to resolve over-segmentation. We, therefore, assume that these works would have similar or higher time and memory consumption compared to MS-TCN++.

In Figure 4, we compare our method with MSTCN++ in terms of the two metrics defined above. MS-TCN++ uses a full-resolution setup, and we show that our model C2F-TCN works best with a sub-sampled version. For a fair comparison, we show our C2F-TCN using a full-resolution set of features (i.e., where the window of temporal pooling is $w_0 = 1$), similar to MS-TCN++, and also compare C2F-TCN with sub-sampling by a factor of 10, (i.e., where $w_0 = 10$ as in our final proposal). The blue curve denotes MSTCN++; the orange curve denotes our C2F-TCN with full-resolution features; the red curve denotes our C2F-TCN with sub-sampled features. The x-axis of each plot shows the batch size.

We increase the batch size from 5 to the maximum that fits in the one single RTX2080 GPU (20 for MS-TCN++, 25 for our model at full resolution, and 400 for sub-sampled features). In a similar setup, with the maximum batch size, the minimum processing time for a single video for MS-TCN++ is 0.11 seconds, while our model is 0.03 seconds at full-resolution and 0.003 seconds when subsampled, i.e. a speedup of more than 30X. In conclusion, we show that our method takes less resources even when we use full resolution features; using sub-sampled features as proposed in our setup allows for even further reduction.

5. Details of Encoder-Decoder Architecture

Here we give the detailed model architecture explained in subsection 3.1. To define our model, we first define a block called double_conv block where double_conv(in_c, out_c) = Conv1D(in_c, out_c, kernel=3, pad=1) $→$ BatchNorm1D(out_c) $→$ ReLU() $→$ Conv1D(out_c, out_c, kernel=3, pad=1) $→$ BatchNorm1D(out_c) $→$ ReLU(); in_c denotes input channel’s dimension and out_c denotes the output channel’s dimension. Using this block, we define
our model $M$ detailed in the Table 6. The output from $\Psi_i$ is then projected to number of classes and followed by a softmax operation to produce probability vectors $p^{(i)}$ as described in subsection 3.1. Our model has a total of 4.08 million trainable parameters.

### 6. Conclusion

We design a temporal encoder-decoder model with a coarse-to-fine ensemble of decoding layers which achieves state-of-the-art performance in temporal segmentation. Our model produces calibrated predictions with better uncertainty measures which is otherwise crucial for real-world deployment. In addition, we propose a simple and computationally effective augmentation strategy at the feature level which significantly improves results. Such an augmentation strategy can be applied in other works in segmentation or sequence processing. Interestingly, our segmentation architecture allows us to achieve state-of-the-art performance in the complex activity recognition task, opening the possibility for further investigation along this front.

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