Speeding up VP9 Intra Encoder with Hierarchical Deep Learning Based Partition Prediction

Somdyuti Paul, Andrey Norkin, and Alan C. Bovik

Abstract—In VP9 video codec, the sizes of blocks are decided during encoding by recursively partitioning 64×64 superblocks using rate-distortion optimization (RDO). This process is computationally intensive because of the combinatorial search space of possible partitions of a superblock. Here, we propose a deep learning based alternative framework to predict the intra-mode superblock partitions in the form of a four-level partition tree, using a hierarchical fully convolutional network (H-FCN). We created a large database of VP9 superblocks and the corresponding partitions to train an H-FCN model, which was subsequently integrated with the VP9 encoder to reduce the intra-mode encoding time. The experimental results establish that our approach speeds up intra-mode encoding by 69.7% on average, at the expense of a 1.71% increase in the Bjøntegaard-Delta bitrate (BD-rate). While VP9 provides several built-in speed levels which are designed to provide faster encoding at the expense of decreased rate-distortion performance, we find that our model is able to outperform the fastest recommended speed level of the reference VP9 encoder for the good quality intra encoding configuration, in terms of both speedup and BD-rate.

Index Terms—VP9, fully convolutional network, hierarchical classification, block partitioning, intra prediction.

I. INTRODUCTION

VP9 has been developed by Google [1] as an alternative to mainstream video codecs such as H.264/AVC [2] and High Efficiency Video Coding (HEVC) [3] standards. VP9 is supported in many web browsers and on Android devices, and is used by online video streaming service providers such as Netflix and YouTube.

As compared to both its predecessor, VP8 [4] and H.264/AVC video codecs, VP9 allows larger prediction blocks, up to size 64×64, which results in a significant improvement in coding efficiency. In VP9, sizes of prediction blocks are decided by a recursive splitting of non-overlapping spatial units of size 64×64, called superblocks. This recursive partition takes place at four hierarchical levels, possibly down to 4×4 blocks, through a search over the possible partitions at each level, guided by a rate-distortion optimization (RDO) process. The Coding tree units (CTUs) in HEVC, which are analogous to VP9’s superblocks, have the same default maximum size of 64×64 and minimum size of 8×8, which can be further split into smaller partitions (4×4 in the intra-prediction case). However, while HEVC intra-prediction only supports partitioning a block into four square quadrants, VP9 intra-prediction also allows rectangular splits. Thus, there are four partition choices at each of the four levels of the VP9 partition tree for each block at that level: no split, horizontal split, vertical split and four-quadrant split. This results in a combinatorial complexity of the partition search space since the square partitions can be split further. A diagram of the recursive partition structure of VP9 is shown in the Fig. [1].

Although the large search space of partitions in VP9 is instrumental to achieve its rate-distortion (RD) performance, it causes the RDO based search to incur more computational overhead as compared to VP8 or H.264/AVC, making the encoding process slower. Newer video codecs, such as AV1 [5] and future Versatile Video Coding (VVC) [6], allow for prediction units of sizes from 128×128 to 4×4, giving rise to even deeper partition trees. As ultra high-definition (UHD) videos become more popular, the need for faster encoding algorithms will only escalate. One important way to approach this issue is to reduce the computational complexity of the RDO-based partition search in video coding.

While state of the art performances in visual data processing technologies, such as computer vision, rely heavily on deep learning, mainstream video coding and compression technology remains dominated by traditional block-based hybrid codecs. However, deep learning based image compression techniques such as [7]–[9] are also being actively explored, and have shown promise. A few of such image based deep learning techniques have also been extended to video compression with promising results [10]–[12]. A second category...
of work uses deep learning to enhance specific aspects of video coding, such as block prediction [13], motion compensation [15], [16], in-loop filtering [17]-[19], and rate control [20], with the objective of improving the efficiency of specific coding tools. Given these developments, there is a possibility of a future paradigm shift in the domain of video coding towards deep learning based techniques. Our present work is motivated by the success of deep learning-based techniques such as [21], [22], on the current and highly practical task of predicting the HEVC partition quad-trees.

In this paper, we take a step in this direction by developing a method of predicting VP9 intra-mode superblock partitions in a novel bottom-up way, by employing a hierarchical fully convolutional network (H-FCN). Unlike previous methods of HEVC partition prediction, which recursively split blocks starting with the largest prediction units, our method predicts block merges recursively, starting with the smallest possible prediction units, which are \(4 \times 4\) blocks in VP9. By taking a bottom-up approach optimized using an H-FCN model we are able to achieve better performance with a much smaller network than [22]. By integrating the trained model with the reference VP9 encoder, we are able to substantially speed up intra-mode encoding at a reasonably low RD cost, as measured by the Bjontegaard delta bitrate (BD-rate) [23], which quantifies differences in bitrate at a fixed encoding quality level relative to another reference encode. Our method also surpasses the higher speed levels of VP9 in terms of speedup, while maintaining a lower BD-rate as we show in the experimental results.

The main steps of our work presented in this paper can be summarized as follows:

1) We created a large and diverse database of VP9 intra encoded superblocks and their corresponding partition trees using video content from the Netflix library.

2) We developed a fast H-FCN model that efficiently predicts VP9 intra-mode superblock partition trees using a bottom-up approach.

3) We integrated the trained H-FCN model with the VP9 encoder to demonstrably speed up intra-mode encoding.

The source code of our model implementation, including the modifications made to the reference VP9 decoder and encoder for creating the database of superblock partitions, and using the trained H-FCN model for faster intra encoding, respectively, is available online at [24].

The rest of the paper is organized as follows. In Section II we briefly review earlier works relevant to the current task. Section III describes the VP9 partition database that we created to drive our deep learning approach. Section IV elaborates the proposed method. Experimental results are presented in Section V. Finally, we draw conclusions and provide directions for future work in Section VI.

II. RELATED WORK

The earliest machine learning based methods that were designed to infer the block partition structures of coded videos from pixel data relied heavily on feature design. A decision tree based approach was used to predict HEVC partition quadtrees for intra frames from features derived from the first and second order block moments in [25], reportedly achieving a 28% reduction in computational complexity along with 0.6% increase in BD-rate. Using a support vector machine (SVM) classifier on features derived from measurements of the variance, color and gradient distributions of blocks, a 36.8% complexity reduction was gained against a 3% increase in BD-rate in [26], on the screen content coding extension of HEVC in the intra-mode.

With the advent of deep learning techniques in recent years, significant further breakthroughs were achieved [21], [22], [27]. In [21], a parallel convolutional neural network (CNN) architecture was employed to reduce HEVC intra encoding time by 61.1% at the expense of a 2.67% increase in BD-rate. Three separate CNN models were used to learn the three-level intra-mode partition structure of HEVC in [27], obtaining an average savings of 62.2% of encoding time against a BD-rate increase of 2.12%. This approach was extended in [22] to reduce the encoding time of both intra and inter modes using a combination of a CNN with a long short-term memory (LSTM) architecture. This approach reduced the average intra-mode encoding time by 56.9-66.5% against an increase of 2.25% in BD-rate, while in the inter mode, a 43.8%-62.9% average reduction was obtained versus an increase of 1.50% in BD-rate.

However, there has been little work reported on the related problem of reducing the computational complexity of RDO based superblock partition decisions in VP9, and even less work employing machine learning techniques. A multi-level SVM based early termination scheme for VP9 block partitioning was adopted in [28], which reduced encoding time by 20-25% against less than a 0.03% increase in BD-rate in the inter mode. Although superblock partition decisions using RDO consume bulk of the compute expense of intra-mode encoding in VP9, to the best of our knowledge, there has been no prior work on predicting the complete partition trees of VP9 superblocks.

The problem of VP9 superblock partition prediction is a hierarchical decision process, which involves choosing one of four types of partitions for each block, at every level of the partition tree. A hierarchical structure was introduced in [29], using a two-level CNN that was trained to perform coarse-to-fine category classification, achieving improvements in the classification accuracy. Based on similar principles, [30] extended the hierarchical classification approach to more than two levels, using a branched CNN model with multiple output layers yielding coarse-to-fine category predictions. The ability of these architectures to capture the hierarchical relationships inherent in visual data motivates our model design. At the same time, unlike global image tasks such as classification, inferring partition trees from superblock pixels is a spatially dense prediction task. For example, on a \(64 \times 64\) superblock, there can be a maximum of \(64 \times 64\) blocks whose partitions are to be inferred. This means that as many as 64 localized predictions must be made on a \(64 \times 64\) superblock at the lowest level of the partition tree.

Fully convolutional networks (FCNs) have been shown to perform remarkably well on a variety of other spatially
dense prediction tasks, such as semantic segmentation [31],
depth estimation [32], saliency detection [33], object
detection [35], visual tracking [36] and dense captioning [37].
Moreover, convolution layers are typically faster than fully
connected layers for similar input and output sizes. Likewise,
we have found that the H-FCN model that we have developed
connected layers for similar input and output sizes. Likewise,
has the ability to simultaneously handle hierarchical prediction and dense prediction with significant
speedup.

III. VP9 Intra-mode Superblock Partition
Database

In order to facilitate a data-driven training of our H-FCN
model, we constructed a large database of VP9 intra encoded
superblocks, corresponding QP values, and partition trees. In
the absence of a publicly available superblock database for
VP9 similar to the one developed in [22] for HEVC CTU
partitions, this was a necessary first step for our work.

A. Partition Tree Representation

Since the number of possible partition trees of a superblock
is too large to be represented as distinct classes in a multi-
class classification problem, we need a simple and concise
description of the partition tree to ensure effective learning.
The partition tree representation we adopt is similar to [22], but
represents block merges instead of splits to facilitate bottom-up
prediction. In our approach, the partition tree is represented by
four matrices \( M_0, \ldots, M_3 \) that correspond to the four levels
of the VP9 partition tree. An example of a superblock partition
tree is illustrated in Fig. 2. The four possible merges of the
blocks at each level (including the possibility of no merge) are
indicated by the numbers 0 to 3 as shown in the Fig. 2. Each
element of the matrices indicates the type of merge of the
group of four blocks corresponding to that element’s location
at that level. For example, each element of the \( 8 \times 8 \) matrix \( M_0 \)
indicates how the four \( 4 \times 4 \) blocks at corresponding locations
are merged at level 0. Similarly, \( M_1, M_2 \) and \( M_3 \) represent
merges of non-overlapping groups of four \( 8 \times 8, 16 \times 16 \) and
\( 32 \times 32 \) blocks, respectively, at the higher levels. We denote the
partition tree of a superblock by \( P = \{ M_0, \ldots, M_3 \} \). This
succinct representation allows us to formulate the problem as
a multi-level, multi-class classification task, with 4 levels, and
4 classes corresponding to each matrix element.

B. Database Creation

Our database was created using content from the Netflix video
catalog, encoded using the reference VP9 encoder from the
libvpx package [38], in VP9 profile 0 (8 bits/sample
and 4:2:0 chroma subsampling), using speed level 1 and the
quality setting good. The contents were drawn from 89
cinematic productions and 17 television episodes, each from
a unique television series. The contents selected were drawn
from different genres, such as action, drama, animation, etc.

We encoded each content at three resolutions: 1920 \( \times \) 1080,
1280 \( \times \) 720 and 960 \( \times \) 540. The partition pattern selected by the
RDO on each superblock depends on both its visual content,
as well as the QP value chosen for that superblock. Thus, we
modified the VP9 decoder from the libvpx package to record
the computed partition tree \( P \) of each superblock, in the form
described in Section III-A along with the corresponding QP
value \( Q \) while decoding the intra frames of the VP9 encoded
bitstreams.

In order to obtain the raw pixel data corresponding to the super-
blocks of each VP9 encoded video, the source videos were
converted to a YCbCr 4:2:0 8-bit representation, then
downsampled to the encode resolution via Lanczos resampling,
if the source and the encode were at different resolutions.
Following this process, the luma channels of non-overlapping
\( 64 \times 64 \) blocks were extracted from the source frames at the
encode resolution. Denote this superblock pixel data by \( S \).
Thus, each sample of our database may be expressed by a
tuple \( (S, Q, P) \). If the frame width or height (or both) is
not exactly divisible by 64, the VP9 encoder zero pads the
frame boundaries to construct superblocks of size \( 64 \times 64 \)
at the boundaries during encoding. However, we excluded the
boundary superblocks with partial zero padding from our
database.

The HEVC intra-mode partition database [22] is limited
to only 4 QP values. By contrast, our database encompasses
internal QP values in the range 8-105, where the internal QP
value range for VP9 is 0-255 (the corresponding external QP
value range is 0-63). The range of QP values used in our
database is a practical range used for encoding intra frames in
adaptive streaming, where rather than using higher QP values
to stream videos at low target bitrates, a lower resolution video
is streamed, which is suitably upsampled later at the viewers’
end [39]. Furthermore, the content of the HEVC intra-mode
partition database of [22] is limited to 2000 images. We
believe that utilizing frames drawn from a diverse collection
of real video content and a range of practical QP values better
supports the development of improved partition prediction
models.

We divided our database into training and validation sets,
as summarized in Table I where the letters M and E indicate
cinematic “movies” and television “episodes,” respectively.
Table I also specifies the percentage of computer graphics
image (CGI) content in each set. Although the superblocks
datastream of Netflix content cannot be made publicly available
(due to the content licenses), we do provide the code for the
modified VP9 decoder at [24], which can be used to generate
a similar database from a set of VP9 encoded bitstreams and

![Fig. 2. Matrix representation of the four-level partition tree.](image)

IV. Proposed Method

As mentioned earlier, in our approach the partition tree is constructed in a bottom-up manner, where merges of the smallest possible blocks, which are of size $4 \times 4$ in VP9, are predicted first at the lowest level of the partition tree, followed by merge predictions on larger blocks at the upper levels. This is unlike the coarse-to-fine approaches used in many image analysis applications, but it is well-motivated here. The intuition behind this strategy is that, since the smaller blocks are more spatially localized, low-level local features, such as edges and corners that are learned by the early layers of a CNN, should be adequate to predict the merge types of $4 \times 4$ blocks i.e. the partition types of $8 \times 8$ blocks. The most notable benefit of this approach is that early prediction of the merge types of the smaller blocks at the lower levels of the partition tree, saves computation time and network parameters that can instead be invested in predicting the merge types of larger blocks at the upper levels, on which the CNN needs to learn more complex patterns. This allows us to design a deeper network for the higher levels, having many fewer trainable parameters than for example, the ETH-CNN of [22] with three parallel branches and 1 287 189 trainable parameters, which uses just three convolutional layers at each level. The most notable benefit of this approach is that early prediction of the merge types of the smaller blocks at the lower levels of the partition tree, saves computation time and network parameters that can instead be invested in predicting the merge types of larger blocks at the upper levels, on which the CNN needs to learn more complex patterns. This allows us to design a deeper network for the higher levels, having many fewer trainable parameters than for example, the ETH-CNN of [22] with three parallel branches and 1 287 189 trainable parameters, which uses just three convolutional layers at each level of prediction, despite the larger number of trainable parameters. A deeper network is able to learn additional levels of hierarchical abstractions of the data, which is relevant in the context of hierarchical partition prediction in VP9.

A. H-FCN architecture

The architecture of our H-FCN model is shown in Fig. 3. It consists of four output branches and a trunk from which the branches emanate. This branched architecture is similar to [30]. However, unlike [30], our model is fully convolutional and uses a bottom up prediction scheme. The inputs to the model are the superblocks $S$ and corresponding QP values $Q$. The trunk has a conventional CNN structure with convolutional layers followed by rectified linear unit (ReLU) nonlinearities [40] and using batch normalization [41]. Also $2 \times 2$ max pooling is applied following every two convolutional layers in the trunk. The outputs of the model are the matrices $M_0, \cdots, M_3$ which constitute the partition tree $P$. Each branch predicts one matrix from the lowest to the highest level of the partition tree, as shown in Fig. 3.

The input to each branch are the features produced by the convolutional layers processed by ReLU, batch normalization and max pooling at each depth of the trunk. At the first layer of each branch, a convolutional layer having filters with spatial kernel dimensions of $4 \times 4$ and stride 4 is used, making it possible to isolate the features corresponding to adjacent blocks at that level. The QP value is fed at the input of the second convolutional layer of each branch by concatenating a matrix of identical elements of value $Q$ to the output of the first convolutional layer (after ReLU and batch normalization operations). The size of this matrix at each branch is chosen to match the spatial dimensions of the output of the first convolutional layer of that branch, which allows the two to be concatenated along their third dimension. Since the features that correspond to adjacent blocks are isolated by the first convolutional layer of each branch, feeding in QP value input in this manner also ensures that there is a copy of the QP value corresponding to the prediction of each block at the subsequent layers of that level. Unlike CNNs that make global predictions using fully connected output layers, we need to make structured local predictions at each branch, except for the last one (at the topmost level of the partition tree). The subsequent output layers of these branches are designed as convolutional layers having $1 \times 1 \times M$ filters, where $M$ is the “depth” dimension of the input to the layers. This design serves to maintain isolation between features that correspond to adjacent blocks by forming local connections to the outputs of the previous layers. At the last branch, the spatial dimension of the input to the first $1 \times 1$ convolutional layer is also $1 \times 1$, which makes it functionally equivalent to a fully connected layer. Finally, the output of the last $1 \times 1$ convolutional layer of each branch is fed to a softmax function, yielding a set of class probabilities.

Using $1 \times 1 \times M$ convolutions on the features derived from each block at particular convolutional layer of each branch, is akin to having a fully connected layer (in the “depth” dimension) for every block at the same level while sharing the weights. This design has two important consequences. First, it increases the inference and training speed as compared to using fully connected layers because of the greatly reduced number of connections. Second, it further speeds up convergence during training by reducing the number of trainable parameters and by “augmenting” the data, since blocks of the same size but at different spatial locations within a superblock are used to train the convolution parameters.

It should be noted that, although we experimented with larger model architectures, we found the architecture of Fig. 3 to be best suited to the task, as elaborated later in Section V. We will refer to the model as shown in Fig. 3 as the “H-FCN model” in the rest of the paper, unless stated otherwise.

B. Loss Function

Since there are four possible types of merges for each group of four blocks at each level, predicting the elements of the matrices $M_0, \cdots, M_3$ is a multi-class classification with four classes. By slicing each of the four matrices into their constituent elements, we obtain a total of 85 outputs. A categorical cross-entropy loss is then applied to each output:

$$ L_q(w) = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{K} y_{i,j} \log(p_{i,j}^q(w)) \quad q = 1, \cdots, 85 \quad (1) $$
where $N$ is the batch size, $K = 4$ is the number of classes, $w$ represents the weights of the network, and $p_{i,j}(w)$ is the softmax probability of the $i$th sample, predicted for the $j$th class at the $q$th output of the network. The net loss of the network is then $L(w) = \sum_{p=1}^{85} L_q(w)$.

C. Integration with VP9 Encoder

We integrated the trained H-FCN model with the reference VP9 encoder implementation, available in the *libvpx* package [38]. By this integration, we replaced the RDO based partition search of the VP9 encoder with the H-FCN model prediction, which, as it turns out, makes intra encoding much faster.

Since the different levels of the superblock partition are modeled independently of one another, the predictions of any two adjacent levels might be mutually inconsistent, producing an invalid partition tree. For example, a “full merge” may be predicted for a group of four $16 \times 16$ blocks at level 2, whereas the four $8 \times 8$ subblocks within one of these $16 \times 16$ blocks can be predicted to have no merge in level 1. This is inconsistent, because in this case the merger of four $16 \times 16$ blocks indicates that a $32 \times 32$ block is not split, and thus the $16 \times 16$ subblocks within it cannot have a split either, although a split is required by the “no merge” prediction of the corresponding group of $8 \times 8$ blocks. Thus, it may be necessary to correct the predictions in $P$ to obtain a valid partition tree that can be used while encoding. We devised a top-down correction procedure that is illustrated in Fig. 4, where the colored regions are inconsistent with predictions at other levels. Consistency is enforced between adjacent levels by correcting any of the other three merge predictions to “full merge,” at all such blocks at the lower of the two levels enclosed by a larger block predicted to have “full merge” at the higher level. Beginning with level 2, predictions at each level are successively corrected to be consistent with its corrected next higher level in this manner. In other words, first $M_2$ at level 2 is corrected to be consistent with $M_3$; let the corrected matrix at level 2 be $M'_2$. At the next step, $M_1$ is corrected to be consistent with $M'_2$ to obtain $M'_1$ and so on. At the end of this procedure, we have $P' = \{M_3, M'_2, M'_1, M'_0\}$, where $P'$ is a valid partition tree.

Although the predictions made by the H-FCN are independent at each level, they were found to be remarkably consistent across levels. Our experiments revealed that only about 5.17% of the predicted superblock partition trees from the validation set were inconsistent, and thus needed the aforementioned correction. This suggests that although the consistency requirement was not explicitly enforced, the H-FCN model implicitly learns to make consistent merge predictions most of the time. The motivation behind our choice of the inconsistency correction approach is explained in Section V-D.

Predictions in $P'$ are then ordered to form a preorder traversal of the partition tree from left to right and top to bottom, which corresponds to the order in which the blocks are encoded in VP9. The predictions thus ordered are then recursively used to replace the RDO module of the encoder to decide the partitions of all the superblocks except those extending beyond frame boundaries. Since these boundary cases were not included in our database, we simply invoke the RDO module to encode them.

V. EXPERIMENTAL RESULTS

In order to experimentally evaluate the performance of our H-FCN model relative to RDO, we compared the encoding
time and RD performance of the two approaches on a set of test video sequences at three different resolutions. To further validate the efficacy of our approach, we also extended the comparison to include the highest recommended speed level of VP9 for our encoding configuration (cpu-used 4 at good quality).

A. System Settings

We developed and trained our H-FCN model using Tensorflow (version 1.12) with the Keras API. The model was trained on a system with an Intel Core i7-6700K CPU @4 GHz, with 8 cores and 32 GB RAM running a 64 bit Ubuntu 16.04 operating system. The training was accelerated with a Nvidia Titan X Pascal GPU with 12 GB of memory.

Since the loss is not calculated during inference, the matrix slicing operation to generate multiple outputs is unnecessary, and removing it reduces the inference time by a significant fraction in our Keras implementation. Thus, we removed the slicing layers during inference as indicated by the dashed box in Fig. 3 directly obtaining the matrices $M_0, \cdots, M_3$ as the network outputs. The trained Keras model was then converted to a Tensorflow computation graph prior to deployment in the VP9 encoder. Integration of the trained model with the reference VP9 encoder was done using libvpx version 1.6.0, which is same as the one used to encode the VP9 bitstreams to create the partition trees in our database. Since the libvpx implementation of VP9 is in C language, we used the Tensorflow C API, which was compiled with support for optimizations that use Intel’s Math Kernel Library for Deep Neural Networks. This enabled us to seamlessly embed our model within the VP9 encoder. The Tensorflow C API was also found to be considerably faster than both Keras and Tensorflow’s native Python API for inference, which is an added advantage of this choice. While a GPU was used for training, all encoding tests were performed without a GPU on a single core Intel Core i7-7500U CPU @2.70GHz with 8 GB of RAM running 64 bit Ubuntu 16.04.

B. Training Details and Hyperparameters

The H-FCN model as depicted in Fig. 3 has 26,336 trainable parameters and executes 54,610 floating point operations (FLOPs) per sample. We also experimented with two larger versions of the model, having 336,608 and 70,408 trainable parameters, which were identical to that in Fig. 3 except that we used a larger number of filters in certain layers.

The number of training and validation samples are as mentioned in Table I. The H-FCN model was trained with a batch size of 128 using the Adam optimizer, with a step size of 0.001 for over $10^5$ iterations. The weights of each layer were initialized with randomly drawn samples from uniform distributions determined by the size of the inputs to each layer. Fig. 5 illustrates the variation of the training and validation losses of the H-FCN model against the number of training iterations, where the validation loss was evaluated on

In Table I we also include the performance results of the two larger models with 336,608 and 70,408 parameters respectively, to show that our model design allows for smaller architectures with no significant impairment of prediction accuracy. From Table I we observe that the maximum decline in accuracy on the validation set between the largest and the smallest models was 1.13%, which occurred at level 2. The impact of this decline in accuracy on the BD-rate is examined in Section V-D. Although direct comparisons against similar models developed for HEVC are difficult since both the codec and the database are different, as a reference, it is worth noting that we were able to achieve better accuracy, on average, with a much smaller model. The ETH-CNN model which has 1,287,189 parameters, achieved an average accuracy of 85.94% across all levels (90.98%, 86.42% and 80.42%, respectively at the three levels of the HEVC quadtree from top to bottom), whereas our H-FCN model, with only 26,336 parameters, achieved a prediction accuracy of 87.51% averaged across all four levels. This improvement can be attributed to the hierarchical prediction strategy and the deeper architecture of our model, as discussed in Section IV.

C. Prediction Performance

We evaluated the prediction accuracy of the trained model on the validation set. The average accuracies of the model at the four levels of prediction were evaluated on $10^5$ randomly drawn samples of the validation set, and are summarized in Table II. The corresponding performance on an equal number of random samples from the training set is also provided for reference.

In Table II we observe that the maximum decline in accuracy on the validation set between the largest and the smallest models was 1.13%, which occurred at level 2. The impact of this decline in accuracy on the BD-rate is examined in Section V-D. Although direct comparisons against similar models developed for HEVC are difficult since both the codec and the database are different, as a reference, it is worth noting that we were able to achieve better accuracy, on average, with a much smaller model. The ETH-CNN model which has 1,287,189 parameters, achieved an average accuracy of 85.94% across all levels (90.98%, 86.42% and 80.42%, respectively at the three levels of the HEVC quadtree from top to bottom), whereas our H-FCN model, with only 26,336 parameters, achieved a prediction accuracy of 87.51% averaged across all four levels. This improvement can be attributed to the hierarchical prediction strategy and the deeper architecture of our model, as discussed in Section IV.

Fig. 5. H-FCN loss with training progress.
D. Encoding Performance

Although the encoding time can be reduced by predicting the block partitions using a trained model instead of conducting RDO-based exhaustive search, the RD performance of learned models may suffer due to incorrect partition predictions. Thus, to evaluate the performance of our trained model, it is also necessary to assess its RD performance with respect to that of the reference RDO. Accordingly, we encoded several test video sequences with the original VP9 encoder using the RDO based partition search, and also with the modified VP9 encoder using the integrated H-FCN model to conduct partition prediction. The test video sequences were obtained as raw videos from multiple publicly available sources commonly used for evaluating video codecs.

A set of five internal QP values \{15, 31, 47, 70, 99\} (corresponding to external QP values of \{20, 30, 35, 40, 45\} respectively) was selected to represent a practical quality range of intra-frames used in adaptive streaming. Each sequence was then encoded at these five QP values in one pass, using constant quality intra-mode, one tile per frame, speed level 1 and the good quality setting. These settings were chosen to be compatible with the encoding configuration used for our database, as mentioned in Section III-B, although our model is equally amenable to be trained for other configurations and can be parallelized over multiple tiles. The RDO based VP9 encoder at these settings thus formed the baseline for our approach. We used the same encoding settings as the baseline for the modified encoder with the integrated H-FCN model.

The percentage speedup of our method with respect to the RDO baseline for a test sequence is calculated as:

$$\Delta T = \frac{T_{RDO} - T_{H-FCN}}{T_{RDO}} \times 100$$

where \(T_{RDO}\) and \(T_{H-FCN}\) are the total times taken to encode the sequence at all five QP values with the RDO baseline encoder and the H-FCN integrated encoder, respectively. Thus, a positive value of \(\Delta T\) represents a speedup with respect to the RDO. To measure the RD performance, we also computed the BD-rate relative to the RDO baseline, using peak signal-to-noise ratio (PSNR) as the distortion metric. Table III reports the \(\Delta T\) and BD-rate values of the test sequences when using the H-FCN models with 336608, 70408 and 26336 parameters.

---

**Table II**

| # of parameters | Training Level 0 | Training Level 1 | Training Level 2 | Training Level 3 | Validation Level 0 | Validation Level 1 | Validation Level 2 | Validation Level 3 |
|-----------------|------------------|------------------|------------------|------------------|-------------------|-------------------|-------------------|-------------------|
| 336608          | 91.96            | 86.63            | 85.70            | 90.54            | 91.43             | 85.70             | 85.70             | 90.80             |
| 70408           | 91.89            | 86.46            | 85.33            | 90.23            | 91.34             | 85.53             | 84.28             | 90.81             |
| 26336           | 91.73            | 86.07            | 84.42            | 89.42            | 91.18             | 85.13             | 83.47             | 90.27             |

---

2 Our test video sequences were sourced from [https://media.xiph.org/video/derf](https://media.xiph.org/video/derf) and [https://tech.ebu.ch/hdtv/hdtv_test-sequences](https://tech.ebu.ch/hdtv/hdtv_test-sequences).
TABLE III  
ENCODING PERFORMANCE OF H-FCN MODEL

| Sequence       | Video Source     | Resolution | # of frames | ΔT | BD-rate |
|----------------|-----------------|------------|-------------|----|---------|
|                 |                 | 1920×1080  |             |    |         |
| Sintel trailer  | Blender         |            | 300         |    | 1.68    |
| Pedestrian area | TUM             |            | 375         |    | 2.61    |
| Sunflower       | TUM             |            | 500         |    | 2.61    |
| Crowd run       | VQEG            |            | 500         |    | 0.99    |
| Ducks takeoff   | VQEG            |            | 500         |    | 1.42    |
| Narrator        | Netflix El fuente |        | 300         |  36.6 | 55.0  |
| Food market     | Netflix El fuente |        | 300         |  37.0 | 65.3  |
| Toddler fountain| Netflix Chimera | 420       |             |    | 0.32    |
| Rainstorms      | EBU             |            | 500         |    | 0.83    |
| Kidscoccer      | EBU             |            | 500         |    | 0.65    |
| Average         |                 | 500        |             |    | 1.46    |
|                 |                 | 1280×720   |             |    |         |
| Big back bunny  | Blender         |            | 300         |  37.6 | 55.2  |
| Park run        | TUM             |            | 504         |  24.0 | 65.2  |
| Shields         | TUM             |            | 504         |  54.2 | 69.3  |
| Into tree       | VQEG            |            | 500         |  52.3 | 69.4  |
| Old town cross  | VQEG            |            | 500         |  59.4 | 77.5  |
| Crosswalk       | Netflix El fuente |        | 300         |  42.4 | 63.3  |
| Tango           | Netflix El fuente |        | 294         |  35.8 | 75.4  |
| Driving POV     | Netflix Chimera |            | 500         |  35.6 | 70.1  |
| Dancers         | Netflix Chimera |            | 500         |  25.5 | 71.9  |
| Vegicandle      | EBU             |            | 500         |  47.1 | 71.6  |
| Average         |                 | 500        |             |    | 1.47    |
|                 |                 | 960×540    |             |    |         |
| Elephant’s dream| Blender         |            | 545         |  37.6 | 54.7  |
| Euro Truck Simulator 2 | Twitch        | 500    |  48.0 | 68.0  |
| Station         | TUM             |            | 313         |  64.0 | 65.4  |
| Rush hour       | TUM             |            | 500         |  27.3 | 50.3  |
| Touchdown pass  | VQEG            |            | 570         |  45.2 | 63.7  |
| Snow mnt        | VQEG            |            | 570         |  35.1 | 50.8  |
| Roller coaster  | Netflix El fuente |        | 500         |  46.1 | 53.6  |
| Dinner scene    | Netflix Chimera |            | 500         |  23.9 | 54.0  |
| Boxing practice | Netflix Chimera |            | 254         |  43.1 | 58.4  |
| Meridian        | Netflix Meridian |         | 500         |  42.4 | 57.9  |
| Average         |                 | -          |             |    | 1.49    |
| Overall Average  |                 | -          |             |    | 1.49    |

TABLE IV  
PERFORMANCE TRADE-OFF OF THE INCONSISTENCY CORRECTION APPROACH WITH RESPECT TO USING RDO TO RESOLVE INCONSISTENCIES

| Resolution | ΔT | BD-rate |
|------------|----|---------|
| 1080p      |    |         |
| Top down   | 67.5 | 63.7  |
| RDO        | 63.7 | 1.70   |
| Top down   | 1.70 | 1.40   |
| 720p       |    |         |
| Top down   | 72.2 | 62.3  |
| RDO        | 62.3 | 1.75   |
| Top down   | 1.75 | 1.13   |
| 540p       |    |         |
| Top down   | 69.5 | 64.1  |
| RDO        | 64.1 | 1.68   |
| Top down   | 1.68 | 1.40   |
| Overall    |    |         |
| Top down   | 69.7 | 63.4  |
| RDO        | 63.4 | 1.71   |
| Top down   | 1.71 | 1.31   |

Continuing our informal comparison with [22] in Section IV-C it is interesting to note that our approach achieves a higher speedup at a lower BD-rate for VP9, than [22] does for HEVC in intra-mode. When the method of [22] was applied to encode video sequences in intra-mode, an average speedup of 61.8% was reported over four QP values (22, 27, 32 and 37) yielding an aggregate BD-rate increase of 2.25%, as compared to the overall average speedup 69.7% achieved by our method with an increase of 1.71% in BD-rate, when encoded at the external QPs values mentioned earlier. It should be noted that the range of quantization levels that can be set while encoding is 0-51 for HEVC whereas it is 0-63 for VP9. Thus, although the quantization levels chosen in the two cases are somewhat different, with [22] being evaluated at higher quantization levels, we believe that the range of QP values chosen in our experiments is better suited for the adaptive streaming, where low target bitrates are achieved by streaming at lower resolutions instead of using higher QP values [39].

We also evaluated the performance trade-off achieved by the top down inconsistency correction scheme described in Section IV-C by exploring an alternative approach of resolving inconsistencies, whereby the RDO was invoked to decide the partitioning of a superblock if its predicted partition tree was determined to be inconsistent. Among all approaches that could be devised to handle inconsistencies, assigning superblocks having inconsistent partition predictions to the RDO in this manner would ensure the best performance in terms of BD-rate, albeit at the possible expense of a decline...
The VP9 encoder provides speed control settings which allow skipping certain RDO search options and using early termination for faster encoding at the expense of RD performance. Thus, we compared the performance of our model with that of speed level 4. Thus, due to its simplicity, we found that the top down approach described in Section IV.C to be a good choice for inconsistency correction.

### E. Comparison with VP9 Speed Levels

The VP9 encoder provides speed control settings which allow skipping certain RDO search options and using early termination for faster encoding at the expense of RD performance. Thus, it essentially works towards the same goal as our H-FCN based partition prediction design. VP9 has 9 speed levels designated by the numerals 0-8. To use a particular speed level, the cpu-used parameter is set to the corresponding number while encoding. The recommended speed levels for best and good quality settings, are 0-4, whereas levels 5-8 are reserved for use with the realtime quality setting. Speed level 0 is the slowest and is rarely used in practice, whereas speed level 1 provides a good quality versus speed trade-off. As already pointed out earlier in this section, speed level 1 with the good quality setting is the baseline for our method, and the fastest encoding for this configuration occurs by setting the speed level to 4.

The experimental results in Table in III show that our model delivers greater improvement in RD performance that can be achieved by reduction in speedup on the sequences tested. Naturally, the inconsistency correction approach against that obtained when the RDO is employed to resolve inconsistencies, for each of the three resolutions considered in our work. Thus, by using the RDO to handle inconsistencies, an overall improvement of 0.4% in BD-rate was achieved at the expense of a 6.3% reduction in speedup on the sequences tested. Naturally, the improvement in RD performance that can be achieved by any other correction scheme is upper bounded by 0.4%, and more sophisticated correction approaches such as those based on prediction probabilities indeed achieved negligible gains. Thus, due to its simplicity, we found that the top down approach described in Section IV.C to be a good choice for inconsistency correction.

#### Table V: Comparison of speedup versus BD-rate tradeoff of our approach with VP9 speed level 4

| Sequence             | Res. | ΔT (%) | BD-rate (in %) | BD-PSNR (dB) |
|----------------------|------|--------|----------------|--------------|
|                      |      | speed 4 | H-FCN | speed 4 | H-FCN | speed 4 | H-FCN | speed 4 | H-FCN |
| Smel trailer         | 1080p| 46.3    | 56.0  | 4.46    | 3.39  | -0.21  | -0.17 |
| Pedestrian area      |      | 62.8    | 61.8  | 2.94    | 2.45  | -0.12  | -0.10 |
| Sunflower            |      | 50.2    | 55.0  | 6.74    | 3.07  | -0.28  | -0.13 |
| Crowd run            |      | 62.8    | 65.3  | 2.30    | 1.16  | -0.21  | -0.11 |
| Ducks takeoff        |      | 63.2    | 67.9  | 1.88    | 1.72  | -0.18  | -0.17 |
| Narrator             |      | 59.5    | 73.3  | 3.72    | 0.58  | -0.13  | -0.02 |
| Food market          |      | 55.9    | 68.5  | 2.39    | 1.63  | -0.18  | -0.12 |
| Toddler fountain     |      | 61.7    | 70.2  | 1.73    | 1.33  | -0.14  | -0.11 |
| Rainroses            |      | 72.9    | 73.5  | 2.50    | 0.92  | -0.14  | -0.04 |
| Kidssoccer           |      | 85.1    | 83.5  | 0.86    | 0.74  | -0.10  | -0.08 |
| Average              |      | 62.0    | 67.5  | 2.95    | 1.70  | -0.17  | -0.10 |
| Big buck bunny       | 720p | 58.4    | 69.3  | 7.92    | 3.21  | -0.51  | -0.21 |
| Parkrun              |      | 61.1    | 65.1  | 3.63    | 1.74  | -0.46  | -0.22 |
| Shields              |      | 70.4    | 69.3  | 2.84    | 1.73  | -0.24  | -0.14 |
| Into tree            |      | 75.6    | 77.0  | 1.57    | 1.27  | -0.13  | -0.11 |
| Old town cross       |      | 75.5    | 77.5  | 2.00    | 1.82  | -0.15  | -0.06 |
| Crosswalk            |      | 71.8    | 74.4  | 3.75    | 1.32  | -0.15  | -0.05 |
| Tango               |      | 62.4    | 75.3  | 2.39    | 1.73  | -0.11  | -0.08 |
| Driving POV          |      | 62.6    | 70.1  | 2.00    | 1.46  | -0.16  | -0.12 |
| Dancers             |      | 70.4    | 71.9  | 12.26   | 2.47  | -0.09  | -0.00 |
| Vegicandle          | 540p | 74.1    | 71.6  | 2.85    | 1.74  | -0.14  | -0.08 |
| Average               |      | 68.2    | 72.2  | 4.12    | 1.75  | -0.21  | -0.11 |
| Elephants dream       |      | 59.2    | 59.9  | 2.13    | 1.82  | -0.18  | -0.16 |
| Euro Truck Simulator 2 | 72.0 | 73.1    | 1.89   | 1.69   | -0.23 | -0.20 |
| Station             |      | 76.5    | 80.7  | 2.06    | 2.27  | -0.13  | -0.15 |
| Rush hour            |      | 59.9    | 66.4  | 2.68    | 1.98  | -0.11  | -0.08 |
| Touchdown pass       |      | 70.1    | 72.8  | 2.56    | 1.62  | -0.15  | -0.09 |
| Snow run             | 540p | 65.2    | 64.6  | 2.31    | 1.04  | -0.30  | -0.14 |
| Roller coaster       |      | 71.1    | 73.9  | 2.21    | 1.68  | -0.15  | -0.11 |
| Dinner Scene         |      | 60.1    | 65.7  | 3.91    | 1.70  | -0.09  | -0.03 |
| Boxing practice      |      | 65.8    | 68.6  | 2.03    | 1.50  | -0.14  | -0.10 |
| Meridian             |      | 59.5    | 69.6  | 1.98    | 1.47  | -0.11  | -0.08 |
| Average               |      | 65.9    | 69.5  | 2.38    | 1.68  | -0.16  | -0.12 |
| Overall Average     |      | 65.4    | 69.7  | 3.15    | 1.71  | -0.18  | -0.11 |

3See [http://wiki.webmproject.org/ffmpeg/vp9-encoding-guide](http://wiki.webmproject.org/ffmpeg/vp9-encoding-guide) for recommended settings.
speedup, while also yielding better RD performance than the available speed control setting of the VP9 codec operating in intra-mode. The computational efficiency of the H-FCN model, combined with the effectiveness of the partitions that it predicts while maintaining good RD performance, implies that it better optimizes this important trade-off than does the VP9 speed control mechanism.

Our approach consistently surpasses the RDO at speed level 4 in terms of speedup achieved over the common baseline, across the practical range of QP values for adaptive streaming considered in our work. To emphasize this point further, Fig. 7 plots the net speedup achieved on the test videos against the QP values, for each of the three spatial resolutions considered. In every instance, the net speedup obtained by using the speed level 4 setting of the VP9 encoder fell below that achieved by our system, over all QP values, although at 540p resolution and QP value of 99, it was very close to that of our method. This strongly supports the utility of our method for practical encoding scenarios that use a range of QP values, rather than a few specific ones.

VI. CONCLUSION

We have developed and explained a deep learning based partition prediction method for VP9 superblocks, that is implemented using a hierarchical fully convolutional network. We constructed a large database of VP9 superblocks and corresponding partitions on real streaming video content from the Netflix library, which we used to train the H-FCN model. The trained model was found to produce consistent partition trees yielding good prediction accuracy on VP9 superblocks. By integrating the trained H-FCN model into the VP9 encoder, we were able to show that VP9 intra-mode encoding time can be reduced by 69.7% on average, at the cost of an increase in intra-mode. The computational efficiency of the H-FCN model, combined with the effectiveness of the partitions that are predicted with inconsistent partitions, the BD-rate was reduced to 1.31% with a corresponding speedup of 63.4%. The experiments we conducted comparing our model against the fastest recommended speed level of VP9 for the good quality setting, further corroborated its effectiveness relative to the faster speed settings available in the reference encoder. This strongly suggests that the framework developed here offers an attractive alternative approach to accelerate VP9 intra-prediction partition search. We also believe that our approach is applicable to other video codecs, such as HEVC and AV1, that employ hierarchical block partitioning at multiple levels.

An immediate next step is to extend our approach to the prediction of inter-mode superblock partitions, a task which encounters the additional challenge of spatiotemporal interference. Further, computing the partition tree, as well as other decisions made by the RDO, may be perceptually suboptimal, since they are generally driven by the goal of optimizing the mean squared error (MSE) with respect to the reference video. Since the MSE is generally a poor indicator of the perceptual quality of images and videos [44], other more perceptually relevant criteria could be considered. By instead optimizing the partition decision process in terms of a suitable perceptual quality model like SSIM [45], MS-SSIM [46], VIF [47], ST-RRED [48], or VMAF [49], [50], RD performance could potentially be further improved, which is a direction that we intend to explore as part of our future work. Finally, it is also interesting to extend this approach to optimize the AV1 codec, which, due to its even deeper partition tree, and more computationally intensive RDO search process, could benefit even more from the speedup offered by our system model.

ACKNOWLEDGMENT

We thank Anush K. Moorthy and Christos G. Bampis of Netflix for their help in creating the database.

REFERENCES

[1] D. Mukherjee et al., “The latest open-source video codec VP9 - An overview and preliminary results,” in Proc. IEEE Picture Coding Symp., 2013, pp. 390–393.
[2] T. Wiegand, G. J. Sullivan, G. Bjontegaard, and A. Luthra, “Overview of the H. 264/AVC video coding standard,” IEEE Trans. Circuits Syst. Video Technol., vol. 13, no. 7, pp. 656–676, 2003.
[3] G. J. Sullivan, J.-R. Ohm, W.-J. Han, and T. Wiegand, “Overview of the high efficiency video coding (HEVC) standard,” IEEE Trans. on Circuits Syst. Video Technol., vol. 22, no. 12, pp. 1649–1668, 2012.
[4] J. Bankoski, P. Wilkins, and Y. Xu, “Technical overview of VP9, an open source video codec for the web,” in Proc. IEEE Int. Conf. Multimedia Expo, 2011, pp. 1–6.
[5] Y. Chen et al., “An overview of core coding tools in the AV1 video codec,” in Proc. IEEE Picture Coding Symp., 2018, pp. 41–45.
[6] B. Bross, J. Chen, and S. Liu, “Versatile video coding (draft 5),” JVET Document JVT-N1001, Geneva, CH, Mar. 2019.
[7] G. Toderici et al., “Full resolution image compression with recurrent neural networks,” in Proc. IEEE Comput. Vision Pattern Recogn., 2017, pp. 5306–5314.
[8] E. Agustsson, M. Tschannen, F. Mentzer, R. Timofte, and L. Van Gool, “Generative adversarial networks for extreme learned image compression,” arXiv preprint arXiv:1804.02958, 2018.
[9] J. Ballé, D. Minnen, S. Singh, S. J. Hwang, and N. Johnston, “Variational image compression with a scale hyperprior,” arXiv preprint arXiv:1802.01436, 2018.
[10] T. Chen, H. Liu, Q. Shen, T. Yue, X. Cao, and Z. Ma, “Deepcoder: a deep neural network based video compression,” in Proc. IEEE Visual Commun. Image Process., 2017, pp. 1–4.
[11] S. Kim et al., “Adversarial video compression guided by soft edge detection,” arXiv preprint arXiv:1811.10677, 2018.
[12] C.-Y. Wu, N. Singhal, and P. Krakenbahi, “Video compression through image interpolation,” in Proc. Euro. Conf. Comput. Vision, 2018, pp. 416–431.
[13] Z. Zhao, S. Wang, S. Wang, X. Zhang, S. Ma, and J. Yang, “Enhanced bi-prediction with convolutional neural network for high efficiency video coding,” IEEE Trans. Circ. Syst. Video Technol., Oct. 2018 (Early Access).
[14] Y. Wang, X. Fan, C. Jia, D. Zhao, and W. Gao, “Neural network based inter prediction for HEVC,” in Proc. IEEE Int. Conf. Multimedia Expo, 2018, pp. 1–6.
[15] J. Liu, S. Xia, W. Yang, M. Li, and D. Liu, “One-for-all: Grouped variation network-based fractional interpolation in video coding,” IEEE Trans. Image Process., vol. 28, no. 5, pp. 2140–2151, May 2019.
[16] Z. Zhao, S. Wang, S. Wang, X. Zhang, S. Ma, and J. Yang, “CNN-based bi-directional motion compensation for high efficiency video coding,” in Proc. IEEE Int. Symp. Circuits Syst., 2018, pp. 1–4.
[17] C. Jia et al., “Content-aware convolutional neural network for in-loop filtering in high efficiency video coding,” IEEE Trans. Image Processing., vol. 26, no. 7, pp. 3343 – 3356, Jul. 2019.
[18] Y. Zhang, T. Shen, X. Ji, Y. Zhang, R. Xiong, and Q. Dai, “Residual highway convolutional neural networks for in-loop filtering in HEVC,” IEEE Trans. Image Process., vol. 27, no. 8, pp. 3827–3841, Mar. 2018.
[19] J. Kang, S. Kim, and K. M. Lee, “Multi-modal/multi-scale convolutional neural network based in-loop filter design for next generation video codec,” in Proc. IEEE Int. Conf. Image Process., 2017, pp. 26–30.
[20] Y. Li, B. Li, D. Liu, and Z. Chen, “A convolutional neural network based approach to rate control in HEVC intra coding,” in Proc. IEEE Vis. Commun. Image Process., 2017, pp. 1–4.
[21] Z. Liu, X. Yu, Y. Gao, S. Chen, X. Ji, and D. Wang, “CU partition mode decision for HEVC hardwired intra encoder using convolution neural network,” IEEE Trans. Image Process., vol. 25, no. 11, pp. 5088–5103, Nov. 2016.
[22] M. Xu, T. Li, Z. Wang, X. Deng, R. Yang, and Z. Guan, “Reducing complexity of HEVC: A deep learning approach,” IEEE Trans. Image Process., vol. 27, no. 10, pp. 5044–5059, Oct. 2018.
[23] G. Bjontegaard, “Calculation of average PSNR differences between RD-curves,” Proc. of the ITU-T V Coding Experts Group (VCEG) Thirteenth Meeting, Apr. 2001.
[24] H-FCN Based VP9 Intra Encoding. Accessed May 27, 2019. [Online]. Available: https://github.com/Somdyut2/H-FCN
[25] D. Ruiz-Coll, V. Adzic, G. Fernandez-Escribano, H. Kalva, J. L. Martinez, and P. Cuenca, “Fast partitioning algorithm for HEVC intra frame coding using machine learning,” in Proc. IEEE Int. Conf. Image Process., 2014, pp. 4112–4116.
[26] F. Duanmu, Z. Ma, and Y. Wang, “Fast CU partition decision using machine learning for screen content compression,” in Proc. IEEE Int. Conf. Image Process., 2015, pp. 4972–4976.
[27] T. Li, M. Xu, and X. Deng, “A deep convolutional neural network approach for complexity reduction on intra-mode HEVC,” in Proc. IEEE Int. Conf. Multimedia Expo, 2017, pp. 1255–1260.
[28] Y. Xian, Y. Wang, Y. Tian, Y. Xu, and J. Bankoski, “Multi-level machine learning-based early termination in VP9 partition search,” Electron. Imaging, vol. 2018, no. 2, pp. 1–5, 2018.
[29] Z. Yan et al., “HD-CNN: hierarchical deep convolutional neural network for large scale visual recognition,” in Proc. IEEE Int. Conf. Multimedia Expo, 2017, pp. 1255–1260.
[30] X. Zhu and M. Bain, “B-CNN: Branch convolutional neural network for hierarchical classification,” arXiv preprint [arXiv:1709.00890], 2017.
[31] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” in Proc. IEEE Conf. Comput. Vision Pattern Recog., 2015, pp. 3341–3340.
[32] V. Badrinarayanan, A. Kendall, and R. Cipolla, “SegNet: A deep convolutional encoder-decoder architecture for image segmentation,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 12, pp. 2481–2495, Dec. 2017.
[33] I. Laina, C. Rupprecht, V. Belagiannis, F. Tombari, and N. Navab, “Deeper depth prediction with fully convolutional residual networks,” in Proc. 4th Int. Conf. 3D Vision, 2016, pp. 239–248.
[34] L. Wang, L. Wang, H. Lu, P. Zhang, and X. Ruan, “Saliency detection with recurrent fully convolutional networks;” in Proc. Euro. Conf. Comput. Vision, 2016, pp. 825–841.
[35] J. Dai, Y. Li, K. He, and J. Sun, “R-FCN: Object detection via region-based fully convolutional networks,” in Proc. Adv. Neural Info. Process. Syst., 2016, pp. 379–387.
[36] L. Wang, W. Ouyang, X. Wang, and H. Lu, “Visual tracking with fully convolutional networks;” in Proc. IEEE Int. Conf. Comput. Vision, 2015, pp. 3119–3127.
[37] J. Johnson, A. Karpathy, and L. Fei-Fei, “DenseCap: Fully convolutional localization networks for dense captioning,” in Proc. IEEE Conf. Comput. Vision Pattern Recogn., 2016, pp. 4565–4574.
[38] libvpx: VP8/VP9 Codec SDK (version 1.6.0). Accessed May 27, 2019. [Online]. Available: https://chromium.googlesource.com/webm/libvpx
[39] A. Aaron, Z. Li, M. Manohara, J. De Cock, and D. Ronca. Per-title encode optimization. Accessed: May 27, 2019. [Online]. Available: https://medium.com/netflix-techblog/per-title-encode-optimization-7e9942062022
[40] X. Glorot, A. Bordes, and Y. Bengio, “Deep sparse rectifier neural networks,” in Proc. 14th Int. Conf. Artif. Intell. Statist., 2011, pp. 315–323.
[41] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” arXiv preprint [arXiv:1502.03167], 2015.
[42] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint [arXiv:1412.6980], 2014.
[43] K. He, X. Zhang, S. Ren, and J. Sun, “Delving deep into rectifiers: Surpassing human-level performance on imagenet classification,” in Proc. IEEE Int. Conf. Comput. Vision, 2015, pp. 1026–1034.
[44] Z. Wang and A. C. Bovik, “Mean squared error: Love it or leave it? a new look at signal fidelity measures,” IEEE Signal Process. Mag., vol. 26, no. 1, pp. 98–117, Jan. 2009.
[45] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, “Image quality assessment: from error visibility to structural similarity,” IEEE Trans. Image Process., vol. 13, no. 4, pp. 600–612, Apr. 2004.
[46] Z. Wang, E. P. Simoncelli, and A. C. Bovik, “Multiscale structural similarity for image quality assessment,” in Proc. 37th Asilomar Conf. Signals, Syst. Comput., vol. 2, 2003, pp. 1398–1402.
[47] H. R. Sheikh and A. C. Bovik, “Image information and visual quality,” IEEE Trans. Image Process., vol. 15, no. 2, pp. 430–444, Feb. 2006.
[48] R. Soundararajan and A. C. Bovik, “Video quality assessment by reduced reference spatio-temporal entropic differencing,” IEEE Trans. Circuits Syst. Video Technol., vol. 23, no. 4, pp. 684–694, 2012.
[49] Z. Li, A. Aaron, J. Katsevounidis, A. Mourth, and M. Manohara, Toward A Practical Perceptual Video Quality Metric. Accessed: May 27, 2019. [Online]. Available: https://medium.com/netflix-techblog/toward-a-practical-perceptual-video-quality-metric-653f208b9652
[50] Z. Li et al. VMAF: The Journey Continues. Accessed: May 27, 2019. [Online]. Available: https://medium.com/netflix-techblog/vmaf-the-journey-continues-44b51ee9ed12