EFFICIENT ATTENTION-FREE VIDEO SHIFT TRANSFORMERS

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ABSTRACT

This paper tackles the problem of efficient video recognition. In this area, video transformers have recently dominated the efficiency (top-1 accuracy vs FLOPs) spectrum. At the same time, there have been some attempts in the image domain which challenge the necessity of the self-attention operation within the transformer architecture, advocating the use of simpler approaches for token mixing. However, there are no results yet for the case of video recognition, where the self-attention operator has a significantly higher impact (compared to the case of images) on efficiency. To address this gap, in this paper, we make the following contributions: (a) we construct a highly efficient & accurate attention-free block based on the shift operator, coined Affine-Shift block, specifically designed to approximate as closely as possible the operations in the MHSA block of a Transformer layer. Based on our Affine-Shift block, we construct our Affine-Shift Transformer and show that it already outperforms all existing shift/MLP–based architectures for ImageNet classification. (b) We extend our formulation in the video domain to construct Video Affine-Shift Transformer (VAST), the very first purely attention-free shift-based video transformer. (c) We show that VAST significantly outperforms recent state-of-the-art transformers on the most popular action recognition benchmarks for the case of models with low computational and memory footprint. Code will be made available.

1 INTRODUCTION

Video recognition is the problem of recognizing specific events of interest (e.g. actions, highlights) in video sequences. Compared to the image recognition problem, video recognition must address at least one additional important technical challenge: the incorporation of the time dimension induces significant computational overheads as, typically, in the best case, a temporal model has $T \times$ more complexity than its corresponding image counterpart ($T$ is the number of frames in the video sequence). For example, existing state-of-the-art models [Fan et al. (2021); Bulat et al. (2021)] still require 400-1000 GFLOPs to achieve high accuracy on the Kinetics dataset [Carreira & Zisserman (2017)]. The main result of this paper is a video recognition model that can achieve similar accuracy while requiring $\sim 3 - 4 \times$ less FLOPs (see also Fig. 1).

Specifically, and following the tremendous success of Transformers in NLP [Vaswani et al. (2017); Chen et al. (2018)], the current state-of-the-art in video recognition is based on video transformers [Bertasius et al. (2021); Arnab et al. (2021); Fan et al. (2021); Bulat et al. (2021)]. While such models have achieved significantly higher accuracy compared to traditional CNN-based approaches (e.g. SlowFast [Feichtenhofer et al. (2019)], TSM [Lin et al. (2019)]), they still require very large video
backbones to achieve these results, e.g., ViT-L/H in [Arnab et al. (2021)]. In fact, the main reason that these models have dominated the accuracy-FLOPs spectrum is because they require significantly fewer number of crops during inference compared to CNN-based approaches.

Concurrently to the development of the aforementioned video transformers, there has been an independent line of research which questions the necessity of the self-attention layers in the vision transformer’s architecture. Such “attention-free” methods have proposed the use of simpler schemes based on MLPs [Touvron et al. (2021a); Chen et al. (2021); Tolstikhin et al. (2021)] and/or the shift operator [Yu et al. (2021b); 2022] for achieving the token mixing effect akin to the self-attention layer. However, these methods have been developed for the image domain, where the cost of the self-attention is relatively low compared to the video domain, where some approximation of the full MHSA is typically necessary. As a result, these methods have not been conclusively shown to outperform self-attention-based transformers for image recognition. Moreover, there are no attention-free methods yet for the case of the video domain where the self-attention operation induces significantly higher computational and memory cost. Hence, the question we wish to address in this paper is: “Can we construct high performing video transformers without attention?”

To address the above question, we make the following contributions:

1. We introduce a new block for attention-free transformers based on the shift operator which is tailored to achieve high accuracy with low computational and memory footprint. Our block, coined Affine-Shift block and shown in Fig. 2 is specifically designed to approximate as closely as possible the operations in the MHSA block of a Transformer layer.

2. Based on our Affine-Shift block, we construct our Affine-Shift Transformer (AST). We exhaustively ablate AST in the image domain for ImageNet classification where we show that it significantly outperforms previous work particularly for the case of low complexity models.

3. By extending our Affine-Shift block in the video domain, we build a new backbone for video recognition, the proposed Video Affine-Shift Transformer (VAST). VAST has two main features: (a) it is attention-free, and (b) it is purely shift-based, effectively applying, for the first time, the shift operation in both space & time to achieve token mixing.

4. We further evaluate VAST on multiple action recognition datasets, namely Kinetics [Carreira & Zisserman (2017)], Something-Something-v2 [Goyal et al. (2017)] and Epic Kitchens [Damen et al. (2018)] where we show that it can achieve similar accuracy to state-of-the-art video transformers, namely [Fan et al. (2021) and Bulat et al. (2021)], while requiring ~ 3 – 4× less FLOPs.
2 RELATED WORK

**Vision Transformers:** After revolutionizing NLP [Vaswani et al. (2017); Raffel et al. (2019)], ViT [Dosovitskiy et al. (2020)] is the first convolution-free transformer that was shown to achieve promising results on ImageNet [Deng et al. (2009)]. Following ViT, a number of notable extensions have been proposed [Touvron et al. (2021b); Liu et al. (2021b); Wang et al. (2021b); Chu et al. (2021); Fan et al. (2021)]. DeiT [Touvron et al. (2021b)] proposes a teacher-student scheme which uses a distillation token so that the student learns from the teacher through attention. PVT [Wang et al. (2021b)] and MViT [Fan et al. (2021)] propose to compute the attention with a sub-sampled version of the input tokens. Swin [Liu et al. (2021b)] introduces non-overlapping local windows for computing the attention and uses a shifted window operation to increase the receptive field. Twins [Chu et al. (2021)] extends PVT in a number of ways emphasizing the importance of using relative positional encodings [Shaw et al. (2018)].

**Attention-free Transformers:** Very recently, the necessity of the self-attention operation within the ViT has been questioned by a number of works which propose spatial token mixing with MLPs [Tolstikhin et al. (2021); Liu et al. (2021a); Touvron et al. (2021a)]. Moreover, such approaches have been further developed by deploying the shift operator [Wu et al. (2018)] and related variants for spatial token mixing giving rise to a number of recently proposed methods [Lian et al. (2021); Chen et al. (2021); Yu et al. (2021b, 2022); Hou et al. (2022)] which are more flexible by allowing the processing of images of different resolutions. AS-MLP [Lian et al. (2021)] proposes an axial shifting strategy where features are spatially shifted in both horizontal and vertical directions. CycleMLP [Chen et al. (2021)] applies the shift operator in a cyclical fashion along the channel dimension. S^2-MLP [Yu et al. (2022)] groups channels together, and shifts each of these groups in a different direction. S^2-MLPv2 [Yu et al. (2021b)] extends S^2-MLP by expanding the channel dimension before shifting and applying a hierarchical pyramid architecture. ViP [Hou et al. (2022)] proposes to permute the height and the width dimension with the channel dimension.

The above works have proposed attention-free architectures in the image domain where the impact of the self-attention operations on the total computational complexity is limited. Hence, the advantage of such architectures over attention-based in terms of efficiency has not been conclusively demonstrated. In our work, we firstly propose the Affine-Shift Transformer (AST), which already outperforms all the above methods in the image domain. Then, we propose to extend it to build the Video Affine-Shift Transformer (VAST), the very first attention-free video transformer which sig-
nificantly outperforms attention-based video transformers, especially for the case of low complexity and memory models.

**Video recognition:** Video recognition has been tackled over the last years using 2D+time [Wang et al. (2018); Lin et al. (2019); Liu et al. (2020)] and 3D CNN-based [Tran et al. (2015); Carrera & Zisserman (2017); Feichtenhofer et al. (2019)] approaches. While the later are characterised by high accuracy thanks to learning strong spatio-temporal models via 3D convolutions, they yield significant computational and memory costs. Somewhere in between are 2D+time works, namely TSM and TAM [Lin et al. (2019); Liu et al. (2020)], that use the shift operator [Wu et al. (2018)] for learning a temporal model at a layer level while still relying on 2D convs.

More recently, a number of video transformers [Bertasius et al. (2021); Arnab et al. (2021); Fan et al. (2021); Bulat et al. (2021)] extending ViT into the video domain were proposed. The main goal of these works has been primarily to reduce the cost of the full space-time attention, which is particularly memory and computationally costly, by using spatio-temporal factorization [Bertasius et al. (2021); Arnab et al. (2021)], low resolution self-attention and hierarchical pyramid architecture [Fan et al. (2021)] and space-time mixing attention [Bulat et al. (2021)].

**Closely related works:** From the above methods, our work is mostly related to Lin et al. (2019); Bulat et al. (2021). Lin et al. (2019) uses the shift operator (Wu et al., 2018) for mixing channels across time while still relying on 2D convs. Bulat et al. (2021) proposes an efficient approximation to the full space-time attention using the shift operator. Therefore, Lin et al. (2019) and Bulat et al. (2021) rely on spatial convolutions and spatial attention, respectively, for processing information in the spatial domain. We go one step beyond and propose VAST which is, to the best of our knowledge, the first video transformer based purely on the shift operator for both space & time processing, further showing significant computational and memory savings without compromising accuracy.

### 3 Method

#### 3.1 Affine-Shift & Video Affine-Shift Block

**Transformer block:** The basic building blocks of the Transformer [Vaswani et al. (2017)] consist of a Multi-Head Self-Attention (MHSA) layer followed by an MLP (with skip connections around them). For any transformer’s layer $l$, they take the form:

$$ Y^l = \text{MHSA}(\text{LN}(X^{l-1})) + X^{l-1}, \quad (1) $$

$$ X^l = \text{MLP}(\text{LN}(Y^l)) + Y^l. \quad (2) $$

where $X^{l-1} \in \mathbb{R}^{S \times d}$ are the input features at layer $l$, $\text{LN}(.)$ is the Layer Norm [Ba et al. (2016)] and the Self-Attention for a single head is given by:

$$ y^l_s = \sum_{s'=0}^{S-1} \sigma(q^l_s \cdot k^l_{s'}) v^l_{s'}, \quad s = 0, \ldots, S - 1 \quad (3) $$

where $\sigma(.)$ is the softmax function, $S$ is the total number of spatial locations, and $q^l_s, k^l_s, v^l_s \in \mathbb{R}^{d_h}$ are the query, key, and value vectors computed from the input features using $W_q, W_k, W_v \in \mathbb{R}^{d \times d}$. The final output is obtained by concatenating and projecting the heads using $W_h \in \mathbb{R}^{d \times d}$ ($d = h d_h$).

We would like to note here that the MLP layers mix channel-wise information within each token, i.e. act independently on each token. Instead, the mixing of information between tokens, i.e. the mixing across spatial dimensions, is exclusively carried out by the MHSA module. Our aim is to find an effective and efficient alternative to the MHSA, i.e. to the token mixing component of Eq. 3.

**Shift operator:** Our goal is to replace the MHSA with an attention-free alternative. One direction that showed promising results as an alternative to convolutions is channel mixing using the shift operator [Wu et al. (2018)]. The main idea is to perform data-mixing by shifting a fixed amount of channels in different directions, such that each feature vector will now contain features from adjacent locations. Note that here the term “directions” depends on the nature of the data (i.e. for
images it can mean up/down, left/right, for videos backward/forward etc.). We will denote with \( \text{Shift}(X, p, b) \) the shifting of \( p \) channels from feature tensor \( X \) across dimensions \( b \in \mathbb{N} \).

**Affine-Shift block:** Our goal is to design an attention-free transformer block, using the shift operator, which approximates as closely as possible the original transformer block. As there is no attention, there is no need to compute queries and values but we will still keep the projection matrix \( W_v \) to compute the values \( V' \) from input features \( X'^{-1} \), i.e., \( V' = \text{LN}(X'^{-1})W_v \).

A naive approach would be to replace Eq. 3 with the \( \text{Shift}(.) \) operator, and note \( b_h \) and \( b_w \) as the width and height dimension indexes:

\[
Z'^l = \text{Shift}(V'^l, p, [b_h, b_w]),
\]

Although this works, as Table 2 shows, it is not sufficient to obtain high accuracy. While the shift operator mixes information across adjacent tokens, the signal is simply mixed but there is no scale or bias adjustment. However, as Eq. 3 shows, in self-attention, the value vectors \( \text{V'}_l \) are scaled by the attention. Moreover, each channel in the output vector \( Y'^l \) is a linear combination of the corresponding channel of the value vectors, suggesting a channel-wise operation.

None of these appear so far in the formulation, suggesting that an extra (channel-wise) operation is missing. To address this, we introduce an Affine-Shift operator, that uses a small MLP to compute a channel-wise rescaling, similar to SE-net [Hu et al. (2018)], and a DWConv to compute a channel-wise bias. Notably, the scale factor and bias are computed from data in a dynamic manner (similar to the dynamic nature of the Transformer block). Moreover, both the MLP and the DWConv take as input the signal post-shifting (as also expected from the Transformer block). The proposed Affine-Shift operation is defined as:

\[
Z'^l = \text{Shift}(V'^l, p, [b_h, b_w]),
\]

\[
\hat{Z}'^l = Z'^l \odot \sigma(\text{MLP}((AVG(Z'^l)))) + \text{DWConv}(Z'^l),
\]

\[
Y'^l = \hat{Z}'^lW_h + X'^{-1}
\]

where \( \odot \) is the Hadamard product, AVG a global average pooling layer and \( \sigma \) the Sigmoid function. Note that both the MLP and 3 × 3 DWConv layer introduce minimal computational overhead. Note that a final linear layer using \( W_h \) is applied as in the original Transformer block.

Putting everything together, the proposed Affine-Shift block firstly applies \( W_v \) to obtain the values by mixing the channels, then the Affine-Shift block to mix tokens and rescale & add bias channel-wise, and finally another projection \( W_h \) to mix again the channels. The block is shown in Fig. 2. Note that all the above mentioned steps are needed to obtain a highly accurate block/architecture. See Table 2 from Section 5.

**Video Affine-Shift:** For video data, we have to mix information across one extra dimension \( \text{i.e.} \) time, its index being noted as \( b_t \). To accommodate this, we can naturally extend the shift operator, described in Eq. 5 as follows:

\[
Z'^l = \text{Shift}(V'^l, p, [b_t, b_h, b_w]),
\]

Effectively, instead of shifting across the last two dimensions (height and width), we shift across all three: time, height, width. Note than unless otherwise specified, the shift is applied uniformly in each (of the 3) direction. We select 1/6 channels for each direction, for a total of 1/2 channels. Both the MLP and the 2D DWConv used to compute a dynamic scale and bias are kept as is.

### 3.2 AST & VAST Architectures

Using the Affine-Shift block and its video extension, we construct the Affine-Shift Transformer (AST), and the Video Affine-Shift Transformer (VAST). We follow the standard hierarchical (pyramidal) structure for our attention-free transformers, where the resolution is dropped between stages, similar to a ResNet [He et al. (2016); Liu et al. (2021b); Fan et al. (2021)]. In all cases we use an overlapping patch embedding across space. For the time dimension the decision to enable overlaps is taken on a case-by-case basis.

For image classification \( \text{i.e.} \) ImageNet, the final predictions are obtained by taking the mean across all tokens and then feeding the obtained feature to a linear classifier. Similarly, for videos, we either
Table 1: Model definitions for the proposed AST and VAST. $E_i$ defines the expansion rate at each stage inside the MLP while the multiplier the number of blocks at the current stage. $C_i$ denotes the number of channels. $T$ is kept constant across stages.

| Stage | Output Size | VAST-Tiny | VAST-Small | VAST-Medium |
|-------|-------------|----------|------------|-------------|
| I     | $H_4 \times W_4$ | $E_1 = 8 \times 3$ | $E_1 = 8 \times 3$ | $E_1 = 8 \times 3$ |
| II    | $H_8 \times W_8$ | $E_2 = 8 \times 4$ | $E_2 = 8 \times 4$ | $E_2 = 8 \times 8$ |
| III   | $H_{16} \times W_{16}$ | $E_3 = 4 \times 8$ | $E_3 = 4 \times 22$ | $E_3 = 4 \times 33$ |
| IV    | $H_{32} \times W_{32}$ | $E_4 = 4 \times 3$ | $E_4 = 4 \times 3$ | $E_4 = 4 \times 3$ |

form a feature representation via global pooling or aggregate the data using the temporal attention aggregation layer proposed in Arnab et al. (2021); Bulat et al. (2021) before passing it to a classifier.

To differentiate between the variants of our model, we align our nomenclature to that of Dosovitskiy et al. (2020) and detail the exact configurations in Table 1.

4 Experimental Details

Datasets: We trained and evaluated our models for large-scale image recognition on ImageNet Deng et al. (2009), and on 4 action recognition datasets, namely on Kinetics-400 and Kinetics-600 Kay et al. (2017), Something-Something-v2 Goyal et al. (2017) and Epic Kitchens-100 Damen et al. (2020). ImageNet experiments aim to confirm the effectiveness of the proposed AST compared to other recently proposed shift-based and MLP-based architectures as these works have not been applied to video domain before. See supplementary material for a description of the datasets.

Training details on Video: All models, unless otherwise stated, were trained following Fan et al. (2021): specifically, our models were trained using AdamW Loshchilov & Hutter (2017) with cosine scheduler Loshchilov & Hutter (2016) and linear warmup for a total of 50 epochs. The base learning rate, set at a batch size of 128, was $2e - 4 \times (4e - 4$ for SSv2) and weight decay was 0.05. To prevent over-fitting we made use of the following augmentation techniques: random scaling (0.08 × to 1.0 ×) and cropping, random flipping (with probability of 0.5; not for SSv2), rand augment Cubuk et al. (2020), color jitter (0.4), mixup ($\alpha = 0.8$) Zhang et al. (2018) and cutmix ($\alpha = 1$) Yun et al. (2019), random erasing Zhong et al. (2020) and label smoothing ($\lambda = 0.1$) Szegedy et al. (2016). During training with a 50% probability we chose between cutmix and mixup. All augmentations are applied consistently across each frame to prevent the introduction of temporal distortions. For Kinetics we set the path dropout rate to 0.1 while on SSv2 to 0.3.

The models were initialised from models pre-trained on ImageNet-1k for Kinetics-400/600 and from Kinetics-400 on Something-Something-v2. When initialising from a 2D model, if a 3D patch embedding is used, we initialized it using the strategy from Fan et al. (2021). We only use a 3D patch embedding for SSv2. The models were trained on 8 V100 GPUs using PyTorch Paszke et al. (2019).

Testing details on Video: Unless otherwise stated, we used 8, 16 or 32 frames. Note that when a 3D stem is used (i.e., on SSv2), the effective temporal dimension is halved. We report results for $1 \times 3$ views (1 temporal clip and 3 spatial crops) following Bertasius et al. (2021); Balat et al. (2021).

5 Ablation Studies

5.1 Affine Shift Analysis and Variations

Firstly we analyse the impact of the three main components described in the Affine-Shift module: the shift operation, the dynamical re-scaling (MLP) and the bias (DWConv) in Eq. 6. As Table 2
shows, replacing the \text{MHSA} with \text{Shift(\_)} (R1) works reasonable well and sets a strong baseline result. Adding the dynamic bias (R2) and scale (R3) on their own improves the result in each case by almost 1.5%. Finally, combining the 3 components together (R4) produces the strongest result. This showcases that all of the introduced components are necessary.

The transformer block consists of \text{MHSA} and \text{MLP} blocks (Eq. 1-2). As we already replaced the \text{MHSA} with \text{Shift(\_)}, a natural question to ask is whether we can further improve the results by adding an additional shift within the \text{MLP} block in the transformer. As the results show (R5), the performance saturates and no additional gains are observed. This suggests that due to the number of layers, the effective receptive size toward the end of the network is sufficiently large to cover the entire image making additional shift operations redundant.

| Block variant                      | Top-1% |
|-----------------------------------|--------|
| (R1) ours - w/o scale & w/o bias | 79.4   |
| (R2) ours - w/o scale             | 80.7   |
| (R3) ours - w/o bias              | 80.9   |
| (R4) ours                         | 81.8   |
| (R5) ours + extra shift           | 81.7   |
| (R6) only shift                   | 79.0   |

Table 2: Effect of various shift-based variants of our method in terms of Top-1 accuracy (%) on ImageNet. See Section 5.1 for details. All models have roughly 3.9 GFLOPs.

A perhaps overlooked detail is the placement of the drop-path. Normally drop-path randomly drops the \text{MHSA} and/or the \text{MLP} block at train time. However, by-passing an Affine-Shift block will result in skipping a data mixing step, effectively producing information with slightly different spatial, temporal, or spatio-temporal context. As such for all of our model, we remove the path drop that affects our Affine-Shift block. Finally, we compare our approach with a more direct alternative, that of replacing Eq. 1 in its entirety with a shift operation. As the results show (R6), while promising, the Affine-Shift block is significantly better.

5.2 How many channels should we shift?

A potentially important factor that could influence the accuracy of the network is the total amount of channels shifted across all dimensions. As the results from Table 3 show, the proposed module is generally robust to the amount of shift within the range 25% - 50%. We note that sustaining the accuracy at lower levels of shift is especially promising for video data, where the number of dimensions we need to shift across increases.

| % channels shift | 0%  | 25% | 33% | 50% |
|------------------|-----|-----|-----|-----|
|                  | 60.2| 81.5| 81.8| 81.7|

Table 3: Impact of the number of shifted channels on the overall accuracy in terms of Top-1 acc (%) on ImageNet.

6 Comparison to state-of-the-art

6.1 ImageNet-1K

In Table 4 we report results on ImageNet for the variant of most interest - tiny (AST-Ti) of our model. Moreover, we report the results of all recently proposed Shift/MLP– and MLP–based backbones. As it can be observed, our tiny model, AST-Ti, is the most accurate among models of similar size with only Cycle-MLP-B2 closely following. Further results and comparison for models sizes: small (AST-S) and medium (AST-B) are reported in the supplementary material.

Note that our goal is not highly-accurate image recognition using very big models but efficient video recognition and hence we did not train or evaluate very big image models. The results of Table 4 clearly show that our model is already a very good candidate for highly accurate and efficient video recognition, outperforming all other Shift/MLP– and MLP–based approaches.
| Arch. | Method                          | #Param | FLOPs | Train Size | Test Size | ImageNet Top-1 |
|------|---------------------------------|--------|-------|------------|-----------|----------------|
|      |                                 | (M)    | (G)   |            |           |                |
| Trans | DeiT-S ([Touvron et al., 2021b]) | 22     | 4.6   | 224        | 224       | 79.9           |
|       | PVTV2-B2-Lt ([Wang et al., 2021a]) | 25     | 3.9   | 224        | 224       | 82.1           |
|       | Swin-T ([Liu et al., 2021b])     | 29     | 4.5   | 224        | 224       | 81.3           |
|       | Focal-T ([Yang et al., 2021])    | 29     | 4.9   | 224        | 224       | 82.2           |
| Hyb.  | CVT-13 ([Wu et al., 2021])       | 20     | 4.5   | 224        | 224       | 81.6           |
|       | CoAtNet-0 ([Dai et al., 2021])   | 25     | 4.2   | 224        | 224       | 81.6           |
|       | LV-ViT-S ([Jiang et al., 2021])  | 26     | 6.6   | 224        | 224       | 83.3           |
| No-attn. | EAMLP-14 ([Guo et al., 2021])    | 30     | −     | 224        | 224       | 78.9           |
|       | ResMLP-S24 ([Touvron et al., 2021a]) | 30     | 6.0   | 224        | 224       | 79.4           |
|       | gMLP-S ([Liu et al., 2021a])     | 20     | 4.5   | 224        | 224       | 79.6           |
|       | GFNet-S ([Rao et al., 2021])     | 25     | 4.5   | 224        | 224       | 80.0           |
|       | GFNet-H-S ([Rao et al., 2021])   | 32     | 4.5   | 224        | 224       | 81.5           |
|       | AS-MLP-T ([Lian et al., 2021])   | 28     | 4.4   | 224        | 224       | 81.3           |
|       | CycleMLP-B2 ([Chen et al., 2021]) | 27     | 3.9   | 224        | 224       | 81.6           |
|       | ViP-Small/7 ([Hou et al., 2022])  | 25     | 6.9   | 224        | 224       | 81.5           |
|       | S2-MLPv2-Small/7 ([Yu et al., 2021b]) | 25     | 6.9   | 224        | 224       | 82.0           |
|       | AST-Ti (Ours)                    | 19     | 3.9   | 224        | 224       | 81.8           |

Table 4: **Comparisons on ImageNet.** Our models are the most accurate within the “No. attn.” category. Hyb. = CNN+Transformer.

| Method                          | Pre-train | Top-1 Acc. (%) | Top-5 Acc. (%) | Frames | Views | FLOPs $\times 10^9$ |
|---------------------------------|-----------|----------------|----------------|--------|-------|---------------------|
| **CNN models**                  |           |                |                |        |       |                     |
| SlowFast ([Feichtenhofer et al., 2019]) | K-400 | 61.7           | -              | 8      | 1 × 3 | 197                 |
| TSM ([R50], [Lian et al., 2019]) | K-400     | 63.3           | 88.5           | 16     | 2 × 3 | 650                 |
| MSNet ([Kwon et al., 2020])     | IN-1k     | 64.7           | 89.4           | 16     |       |                     |
| TEA ([Li et al., 2020])         | IN-1k     | 65.1           | 89.9           | 16     | 10 × 3| 2,100               |
| bLVNet ([Fan et al., 2019])     | IN-1k     | 65.2           | 90.3           | 32     | 10 × 3| 3,870               |
| CT-Net ([Li et al., 2021])      | IN-1k     | 65.9           | 90.1           | 16     | 2 × 3 | 450                 |
| TAdaConvNeXt-T ([Huang et al., 2022]) | K-400 | 67.1           | 90.4           | 32     | 2 × 3 | 564                 |
| **Transformer and Hybrid models** |           |                |                |        |       |                     |
| TimeSformer ([Bertasius et al., 2021]) | IN-21k | 59.5           | -              | 96     | 1 × 3 | 590                 |
| TimeSformer-L ([Bertasius et al., 2021]) | IN-21k | 62.4           | -              | 96     | 1 × 3 | 7,140               |
| ViViT-L/16x2 ([Arnab et al., 2021]) | IN-21k+K-400 | 65.4         | 89.8           | 32     | 4 × 3 | 17,352              |
| XViT-B ([Balat et al., 2021])   | IN-21k    | 66.2           | 90.6           | 16     | 1 × 3 | 850                 |
| XViT-V ([Balat et al., 2021])   | K-600     | 67.2           | 90.8           | 16     | 1 × 3 | 850                 |
| MVIT-B (32 × 4) ([Fan et al., 2021]) | K-400 | 64.7           | 89.2           | 16     | 1 × 3 | 211                 |
| Mformer-H ([Fan et al., 2021])  | IN-21k+K-400 | 66.5        | 90.1           | -      | 1 × 3 | 1,110               |
| Mformer-HR ([Fan et al., 2021]) | IN-21k+K-400 | 68.1        | 90.8           | -      | 1 × 3 | 3,555               |
| Swin-B ([Liu et al., 2021b])    | IN-21k+K-400 | 69.6        | 92.7           | -      | 1 × 3 | 963                 |
| **MLP models (Attention-free transformers)** |           |                |                |        |       |                     |
| VAST-Ti (Ours)                  | K-400     | 67.8           | 90.8           | 16     | 1 × 3 | 98                  |
| VAST-Ti (Ours)                  | K-400     | 69.3           | 91.3           | 32     | 1 × 3 | 196                 |
| VAST-S (Ours)                   | K-400     | 68.7           | 91.0           | 16     | 1 × 3 | 169                 |
| VAST-S (Ours)                   | K-400     | 70.9           | 92.1           | 32     | 1 × 3 | 338                 |

Table 5: Comparison with CNN-based methods and state-of-the-art video transformers on Something-Something-v2. Our tiniest model VAST-Ti-8 largely outperforms the lightest MVIT (+2%) while utilizing 2× fewer FLOPs, and it is only 0.4% behind than the lightest XViT while utilizing less than 4× fewer FLOPs. Larger models show improved accuracy inducing only modest computational overheads, outperforming prior results by a large margin.

6.2 **VIDEO ACTION RECOGNITION**

We report the accuracy achieved by 4 different variants of our models: tiny and small for both 8 and 16 frames, that is VAST-Ti-8, VAST-Ti-16 & VAST-S-8, VAST-S-16. Our models were initialized...
Table 6: Comparison with CNN-based methods and state-of-the-art video transformers on Kinetics-400. Our tiniest model VAST-Ti-8 largely outperforms the lightest MVIT (+2%) while utilizing 2× fewer FLOPs, and it is only 0.4% behind the lightest XViT while utilizing less than 4× fewer FLOPs. Our biggest model VAST-S-16 matches the best XViT model while utilizing less than 2× fewer FLOPs.

with ImageNet-1K pre-training for K-400 and K-600, while for SSv2 we used the models trained on K-400. For SSv2, we use a 3D stem, reducing the temporal dimensionality by 2. Thus, if for example we note 32 input frames, the actual configuration (and cost) corresponds to the 16-frame VAST variants.

We compare with the state-of-the-art in video recognition: In addition to classic CNN-based approaches, we compare against early attempts in video transformers, namely TimeSformer [Bertasius et al., 2021], ViViT [Arnab et al., 2021] and VidTr [Zhang et al., 2021], Mformer [Patrick et al., 2021], the video version of the Swin Transformer [Liu et al., 2021] as well as the state-of-the-art, namely MVIT [Fan et al., 2021] and XViT [Bulat et al., 2021]. For all of these models, we have included both light and heavy versions.

K-400 & K-600: Table 6 shows our results on K-400. It can be seen that our tiny model VAST-Ti-8 largely outperforms all early approaches to video transformers [Bertasius et al., 2021], [Arnab et al., 2021], [Patrick et al., 2021], [Liu et al., 2021], as well as the lightest version of MVIT (+2%) while utilizing 2× fewer FLOPs, and it is only 0.4% behind the most efficient version of XViT (initialized in ImageNet-21K) while utilizing less than 4× fewer FLOPs. Moreover, our larger models show improved accuracy, inducing only modest computational overheads. Our biggest model VAST-S-16 matches the best XViT model while utilizing less than 2× fewer FLOPs. See supplementary material for results on K-600, where we draw similar conclusions.
of accuracy vs FLOPs) without using any attention layers at all.

**SSv2:** On **SSv2**, we firstly emphasize that initialization plays a very important role and that models initialized on different dataset are hard to compare. In light of this, and since we pre-trained our models on K-400, only comparisons with methods pre-trained there (and potentially on K-600) are meaningful. As Table 5 shows, our models significantly outperform all other models in terms of accuracy vs FLOPs. For example, our lightest model (VAST-Ti) outperforms the lightest XViT and MViT by 3.4% and 3.1% while utilizing less than 4× and 2× fewer FLOPs, respectively. Again, our larger models show significant accuracy improvements inducing only modest computational overheads, outperforming other models by large margin.

**Epic-100:** Similar conclusions can be drawn by observing our results on **Epic-100**; see supplementary material.

7 CONCLUSIONS

In the paper’s introduction we posed the question “can we construct high performing video transformers without attention?” The results provided in our results section clearly demonstrated that the answer to this question is positive. To this end, we introduced a new purely shift-based block coined Affine-Shift, specifically designed to approximate as closely as possible the operations in the MHSA block of a Transformer layer. Based on our Affine-Shift block, we constructed AST and show that it outperforms previous work particularly for the case of low complexity models. By extending our Affine-Shift block in the video domain, we built VAST and then showed that it is significantly more efficient than existing state-of-the-art video transformers.

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A Appendix

B Datasets

We trained and evaluated our models for large-scale image recognition on ImageNet [Deng et al. (2009)], and on 4 action recognition datasets, namely on Kinetics-400 and Kinetics-600 [Kay et al. (2017)], Something-Something-v2 [Goyal et al. (2017)] and Epic Kitchens-100 [Damen et al. (2020)]. ImageNet experiments aim to confirm the effectiveness of the proposed AST compared to other recently proposed shift-based and MLP-based architectures as these works have not been applied to video domain before.

**ImageNet**: We used the standard ImageNet-1K consisting of 1.2M training images and 50K validation images belonging to 1K classes.

**Kinetics-400 & 600**: The Kinetics-400 (K-400) and 600 (K-600) datasets consist of pre-segmented YouTube clips, typically of duration of up to 10 seconds, labeled with 400 and 600 classes of human activities, respectively. As many of the original clips are no longer available, we used the ones made available by the CVD foundation[^2]. Due to the nature of the data and the actions being performed, video models strongly relying on appearance-only information already perform very well on these datasets.

**Something-Something-v2**: The Something-Something-v2 (SSv2) dataset consists of more than 220K videos of duration between 2 and 6 seconds depicting humans performing basic actions with everyday objects. Unlike Kinetics, the dataset tends to favor models with strong temporal modeling due to the nature of the actions being performed and the fact that the objects and the backgrounds in the videos are consistent across the classes.

**Epic Kitchens-100**: The dataset is labeled using 97 verb classes and 300 noun classes. The evaluation results are reported using the standard action recognition protocol: the network predicts the “verb” and the “noun” using two heads. The predictions are then merged to construct an “action” which is used to report the accuracy.

C Additional results on Epic Kitchens 100

In addition to the results reported on Kinetics-400/600 and Something-Something-v2, herein we report results on the Epic Kitchens 100 dataset. As the results from Table 7 show, our method matches and outperforms significantly bigger models, pretrained on larger datasets.

[^2]: [https://github.com/cvdfoundation/kinetics-dataset](https://github.com/cvdfoundation/kinetics-dataset)
| Method                      | Pre-train | Action Acc. (%) | Verb Acc. (%) | Noun Acc. (%) |
|-----------------------------|-----------|-----------------|---------------|---------------|
| **CNN models**              |           |                 |               |               |
| TSN (Wang et al., 2018)     | IN-1k     | 33.2            | 60.2          | 46.0          |
| TRN (Zhou et al., 2018)     | IN-1k     | 35.3            | 65.9          | 44.4          |
| TBN (Kazakos et al., 2019)  | IN-1k     | 36.7            | 66.0          | 47.2          |
| TSM (Lin et al., 2019)      | K400      | 38.3            | 67.9          | 49.0          |
| SlowFast (Feichtenhofer et al., 2019) | K400 | 38.5          | 65.6          | 50.0          |
| **Transformer models**      |           |                 |               |               |
| ViViT-L/16x2 (Arnab et al., 2021) | IN-21k + K400 | 44.0          | 66.4          | 56.8          |
| Mformer (Patrick et al., 2021) | IN-21k + K400 | 43.1          | 66.7          | 56.5          |
| Mformer-HR (Patrick et al., 2021) | IN-21k + K400 | 44.5          | 67.0          | 58.5          |
| XViT-B (x8) (Bulat et al., 2021) | IN-21k + K400 | 41.5          | 66.7          | 53.3          |
| XViT-B (x16) (Bulat et al., 2021) | IN-21k + K400 | 44.3          | 68.7          | **56.4**      |
| **MLP models (Attention-free transformers)** |           |                 |               |               |
| VAST-Ti (x8) (Ours)         | K400      | 42.3            | 69.3          | 54.0          |
| VAST-Ti (x16) (Ours)        | K400      | **45.0**        | **70.0**      | 56.0          |

Table 7: Comparison with CNN-based methods and state-of-the-art video transformers on Epic Kitchens 100.
| Arch. | Method | #Param | FLOPs | Train Size | Test Size | ImageNet Top-1 |
|-------|--------|--------|-------|------------|-----------|----------------|
| CNN   | RegNetY-4G (Radosavovic et al., 2020) | 21     | 4.0   | 224        | 224       | 80.0           |
|       | EfficientNet-B5 (Tan & Le, 2019)   | 30     | 9.9   | 456        | 456       | 83.6           |
|       | EfficientNetV2-S (Tan & Le, 2021)  | 22     | 8.5   | 384        | 384       | 83.9           |
| Trans | DeiT-S (Touvron et al., 2021b)     | 22     | 4.6   | 224        | 224       | 79.9           |
|       | PVTv2-B2-Li (Wang et al., 2021a)   | 25     | 3.9   | 224        | 224       | 82.1           |
|       | Swin-T (Liu et al., 2021b)         | 29     | 4.5   | 224        | 224       | 81.3           |
|       | Focal-T (Yang et al., 2021)        | 29     | 4.9   | 224        | 224       | 82.2           |
| Hyb.  | CvT-13 (Wu et al., 2021)           | 20     | 4.5   | 224        | 224       | 81.6           |
|       | CoAtNet-0 (Dai et al., 2021)       | 25     | 4.2   | 224        | 224       | 81.6           |
|       | LV-ViT-S (Jiang et al., 2021)      | 26     | 6.6   | 224        | 224       | 83.3           |
| No-attn. | EAMLP-14 (Guo et al., 2021) | 30     | −     | 224        | 224       | 78.9           |
|       | ResMLP-S24 (Touvron et al., 2021a) | 30     | 6.0   | 224        | 224       | 79.4           |
|       | gMLP-S (Liu et al., 2021a)         | 20     | 4.5   | 224        | 224       | 79.6           |
|       | GFNet-S (Rao et al., 2021)         | 25     | 4.5   | 224        | 224       | 80.0           |
|       | GFNet-H-S (Rao et al., 2021)       | 32     | 4.5   | 224        | 224       | 81.5           |
|       | AS-MLP-T (Lian et al., 2021)       | 28     | 4.4   | 224        | 224       | 81.3           |
|       | CycleMLP-B2 (Chen et al., 2021)    | 27     | 3.9   | 224        | 224       | 81.6           |
|       | ViP-Small/7 (Hou et al., 2022)     | 25     | 6.9   | 224        | 224       | 81.5           |
|       | S2-MLPv2-Small/7 (Yu et al., 2021b) | 25    | 6.9  | 224        | 224       | 82.0           |
|       | AST-Ti (Ours)                      |        |       |            |           |                |
| CNN   | RegNetY-8G (Radosavovic et al., 2020) | 39     | 8.0   | 224        | 224       | 81.7           |
|       | EfficientNet-B7 (Tan & Le, 2019)   | 66     | 39.2  | 600        | 600       | 84.3           |
|       | EfficientNetV2-M (Tan & Le, 2021)  | 54     | 25.0  | 480        | 480       | 85.1           |
| Trans | PVT-B4 (Wang et al., 2021a)        | 62.6   | 10.1  | 224        | 224       | 83.6           |
|       | Swin-S (Liu et al., 2021b)         | 50     | 8.7   | 224        | 224       | 83.0           |
|       | Focal-S (Yang et al., 2021)        | 51     | 9.1   | 224        | 224       | 83.5           |
| Hyb.  | CvT-21 (Wu et al., 2021)           | 32     | 7.1   | 224        | 224       | 82.5           |
|       | CoAtNet-1 (Dai et al., 2021)       | 42     | 8.4   | 224        | 224       | 83.3           |
|       | LV-ViT-M (Jiang et al., 2021)      | 56     | 16.0  | 224        | 224       | 84.1           |
| No-attn. | MLP-mixer (Tolstikhin et al., 2021) | 59     | 11.6  | 224        | 224       | 76.4           |
|       | EAML-P-19 (Guo et al., 2021)       | 55     | −     | 224        | 224       | 79.4           |
|       | S2-MLP-deep (Yu et al., 2022)      | 51     | 10.5  | 224        | 224       | 80.7           |
|       | CCS-MLP-36 (Yu et al., 2021a)      | 43     | 8.9   | 224        | 224       | 80.6           |
|       | GFNet-B (Rao et al., 2021)         | 43     | 7.9   | 224        | 224       | 80.7           |
|       | GFNet-H-B (Rao et al., 2021)       | 54     | 8.4   | 224        | 224       | 82.9           |
|       | AS-MLP-S (Lian et al., 2021)       | 50     | 8.5   | 224        | 224       | 83.1           |
|       | CycleMLP-B4 (Chen et al., 2021)    | 52     | 10.1  | 224        | 224       | 83.0           |
|       | ViP-Medium/7 (Hou et al., 2022)    | 50     | 16.3  | 224        | 224       | 82.7           |
|       | S2-MLPv2-Medium/7 (Yu et al., 2021b) | 55    | 16.3  | 224        | 224       | 83.6           |
|       | AST-S (Ours)                       | 38     | 6.8   | 224        | 224       | 82.8           |
|       | AST-B (Ours)                       | 53     | 10.2  | 224        | 224       | 83.2           |

Table 8: Comparisons on ImageNet. Our models are the most accurate within the “No. attn.” category. Hyb. = CNN+Transformer.
| Method                        | Pre-train | Top-1 Acc. (%) | Top-5 Acc. (%) | Frames | Views | FLOPs $\times 10^9$ |
|------------------------------|-----------|----------------|----------------|--------|-------|---------------------|
| **CNN models**               |           |                |                |        |       |                     |
| LGD-3D R101                  | IN-1k     | 81.5           | 95.6           | –      | –     | –                   |
| SlowFast (Feichtenhofer et al., 2019) | –         | 80.4           | 94.8           | 8      | $10 \times 3$ | 3,180              |
| SlowFast+NL (Feichtenhofer et al., 2019) | –         | 81.8           | 95.1           | 16     | $10 \times 3$ | 7,020              |
| X3D-M (Feichtenhofer, 2020)  | –         | 78.8           | 94.5           | –      | $10 \times 3$ | 186                |
| X3D-XL (Feichtenhofer, 2020) | –         | 81.9           | 95.5           | –      | $10 \times 3$ | 1,452              |
| **Transformer and Hybrid models** |           |                |                |        |       |                     |
| TimeSformer (Bertasius et al., 2021) | IN-1k     | 79.1           | 94.4           | 8      | $1 \times 3$ | 590                |
| TimeSformer-HR (Bertasius et al., 2021) | IN-21k    | 81.8           | 95.8           | 8      | $1 \times 3$ | 590                |
| TimeSformer-L (Bertasius et al., 2021) | IN-21k    | 82.2           | 95.6           | 96     | $1 \times 3$ | 7,140              |
| ViViT-L/16x2 (Arnab et al., 2021) | IN-21k    | 82.9           | 94.6           | 32     | $4 \times 3$ | 17,352             |
| Mformer (Patrick et al., 2021) | IN-21k    | 81.6           | 95.6           | –      | $10 \times 3$ | 11,070             |
| Mformer-HR (Patrick et al., 2021) | IN-21k    | 82.7           | 65.1           | –      | $10 \times 3$ | 28,764             |
| XViT-B (Bulat et al., 2021) | IN-21k    | 82.5           | 95.4           | 8      | $1 \times 3$ | 425                |
| XViT-B (Bulat et al., 2021) | IN-21k    | 84.5           | 96.3           | 16     | $1 \times 3$ | 850                |
| MViT-B (16 \times 4) (Fan et al., 2021) | –         | 82.1           | 95.7           | 16     | $1 \times 5$ | 352                |
| MViT-B (32 \times 3) (Fan et al., 2021) | –         | 83.4           | 96.3           | 32     | $1 \times 5$ | 850                |
| Swin-B (Liu et al., 2021c) | IN-21k    | 84.0           | 96.5           | –      | $4 \times 3$ | 3,384              |
| Swin-L (384) (Liu et al., 2021c) | IN-21k    | 86.1           | 97.3           | –      | $10 \times 5$ | 105,350            |
| **MLP models (Attention-free transformers)** |           |                |                |        |       |                     |
| VAST-Ti (Ours)              | IN-1k     | 82.8           | 94.5           | 8      | $1 \times 3$ | 98                 |
| VAST-S (Ours)               | IN-1k     | 84.0           | 95.5           | 8      | $1 \times 3$ | 169                |

Table 9: Comparison with CNN-based methods and state-of-the-art video transformers on Kinetics-600. Our tiny model VAST-Ti-8 outperforms the lightest version of MViT (+0.7%) while utilizing $4 \times$ fewer FLOPs, and even outperforms the most efficient version of XViT (+0.3%) while utilizing less than $4 \times$ fewer FLOPs.
| Method | Pre-train | Top-1 Acc. (%) | Top-5 Acc. (%) | Frames | Views | FLOPs $\times 10^9$ |
|--------|-----------|---------------|---------------|--------|-------|-------------------|
|        | CNN models |               |               |        |       |                   |
| bLVNet (Fan et al., 2019) | - | 73.4 | 91.2 | $24 \times 2$ | $3 \times 3$ | 840 |
| STM (Jiang et al., 2019) | IN-1k | 73.7 | 91.6 | 16 | - | - |
| TEA (Li et al., 2020) | IN-1k | 76.1 | 92.5 | 16 | $10 \times 3$ | 2,100 |
| TSM (R50) (Lin et al., 2019) | IN-1k | 74.7 | - | 16 | $10 \times 3$ | 650 |
| 13D-NL | IN-1k | 77.7 | 93.3 | 128 | $10 \times 3$ | 10,800 |
| CorrNet-101 | - | 79.2 | - | 32 | $10 \times 3$ | 6,700 |
| ip-CSN-152 | - | 79.2 | 93.3 | 8 | $10 \times 3$ | 3,270 |
| LGD-3D R101 | - | 79.4 | 94.4 | 16 | - | - |
| SlowFast (Feichtenhofer et al., 2019) | - | 78.7 | 93.5 | 8 | $10 \times 3$ | 3,480 |
| SlowFast (Feichtenhofer et al., 2019) | - | 79.8 | 93.9 | 16 | $10 \times 3$ | 7,020 |
| X3D-S (Feichtenhofer, 2020) | - | 72.9 | 90.5 | - | $10 \times 3$ | 58 |
| X3D-L (Feichtenhofer, 2020) | - | 76.8 | 92.5 | - | $10 \times 3$ | 551 |
| X3D-XXL (Feichtenhofer, 2020) | - | 80.4 | 94.6 | - | $10 \times 3$ | 5,823 |
| Transformer models |               |               |               |        |       |                   |
| TimeSformer (Bertasius et al., 2021) | IN-1k | 75.8 | - | 8 | $1 \times 3$ | 590 |
| TimeSformer-L (Bertasius et al., 2021) | IN-21k | 78.0 | 94.7 | 96 | $1 \times 3$ | 7,140 |
| ViViT-B/16x2 (Arnab et al., 2021) | IN-21k | 80.7 | 94.7 | 32 | $4 \times 3$ | 3,408 |
| ViViT-M/16x2 (Arnab et al., 2021) | IN-21k | 80.6 | 94.7 | 32 | $4 \times 3$ | 17,352 |
| Mformer (Patrick et al., 2021) | IN-21k | 79.7 | 94.2 | - | $10 \times 3$ | 11,070 |
| Mformer-HR (Patrick et al., 2021) | IN-21k | 81.1 | 95.2 | - | $10 \times 3$ | 28,764 |
| XViT-B (Bulat et al., 2021) | IN-21k | 78.4 | 93.7 | 8 | $1 \times 3$ | 425 |
| XViT-B (Bulat et al., 2021) | IN-21k | 80.2 | 94.7 | 16 | $1 \times 3$ | 850 |
| MViT-S (Fan et al., 2021) | - | 76.0 | 92.1 | - | $1 \times 5$ | 165 |
| MViT-B (64 $\times$ 3) (Fan et al., 2021) | - | 78.4 | 93.5 | 16 | $1 \times 5$ | 352 |
| En-VidTr-S (Zhang et al., 2021) | IN-21k | 79.4 | 94.0 | 8 | $10 \times 3$ | 3,900 |
| En-VidTr-M (Zhang et al., 2021) | IN-21k | 79.7 | 94.2 | 16 | $10 \times 3$ | 6,600 |
| En-VidTr-L (Zhang et al., 2021) | IN-21k | 80.5 | 94.6 | 32 | $10 \times 3$ | 11,760 |
| Swin-T (Liu et al., 2021c) | IN-1k | 78.8 | 93.6 | - | $4 \times 3$ | 1,056 |
| Swin-S (Liu et al., 2021c) | IN-1k | 80.6 | 94.5 | - | $4 \times 3$ | 1,992 |
| Swin-B (Liu et al., 2021c) | IN-1k | 80.6 | 94.6 | - | $4 \times 3$ | 3,384 |
| Swin-L (384) (Liu et al., 2021c) | IN-21k | 84.9 | 96.7 | - | $10 \times 5$ | 105,350 |
| MLP models (Attention-free transformers) |               |               |               |        |       |                   |
| VAST-Ti (Ours) | IN-1k | 78.0 | 93.2 | 8 | $1 \times 3$ | 98 |
| VAST-Ti (Ours) | IN-1k | 79.0 | 93.8 | 16 | $1 \times 3$ | 196 |
| VAST-S (Ours) | IN-1k | 78.9 | 93.8 | 8 | $1 \times 3$ | 169 |
| VAST-S (Ours) | IN-1k | 80.0 | 94.5 | 16 | $1 \times 3$ | 338 |

Table 10: Comparison with CNN-based methods and state-of-the-art video transformers on Kinetics-400. Our tiniest model VAST-Ti-8 largely outperforms the lightest MViT (+2%) while utilizing $2 \times$ fewer FLOPs, and it is only 0.4% behind than the lightest XViT while utilizing less than $4 \times$ fewer FLOPs. Our biggest model VAST-S-16 matches the best XViT model while utilizing less than $2 \times$ fewer FLOPs.