Trailers12k: Improving Transfer Learning with a Dual Image and Video Transformer for Multi-label Movie Trailer Genre Classification

Ricardo Montalvo-Lezama, Berenice Montalvo-Lezama, Gibran Fuentes-Pineda

Abstract

In this paper, we propose Dual Image and Video Transformer Architecture (DIViTA) for multi-label movie trailer genre classification. DIViTA performs an input adaption stage that uses shot detection to segment the trailer into highly correlated clips, providing a more cohesive input that allows to leverage pretrained ImageNet and/or Kinetics backbones. We introduce Trailers12k, a movie trailer dataset with manually verified title-trailer pairs, and present a transferability study of representations learned from ImageNet and Kinetics to Trailers12k. Our results show that DIViTA can reduce the gap between the spatio-temporal structure of the source and target datasets, thus improving transferability. Moreover, representations learned on either ImageNet or Kinetics are comparatively transferable to Trailers12k, although they provide complementary information that can be combined to improve classification performance. Interestingly, pretrained lightweight ConvNets provide competitive classification performance, while using a fraction of the computing resources compared to heavier ConvNets and Transformers.

Keywords: Multi-label movie trailer genre classification, Transfer learning, Video dataset, Spatio-temporal representations, Video understanding, Transformers, Resource efficient architectures

1. Introduction

Transfer learning (TL) has been fundamental for the success of deep learning. Prominently, it has enabled state-of-the-art performance on a wide range of tasks, particularly when only small training sets are available. In TL, a model is pretrained on a large source dataset and later is adapted to solve a target task on another dataset. The success of TL in computer vision tasks has been mainly driven by the availability of large and diverse source datasets. For several image analysis tasks, image classification (IC) on ImageNet [10] is a standard pretraining practice. Similarly, ImageNet pretraining has been commonly leveraged to initialize video analysis models, especially for human action recognition (HAR). On the other hand, human action recognition...
has been the main video pretraining task for TL on video analysis tasks. As opposed to the image domain, in the video domain different datasets (e.g., UCF [43], Kinetics [19], or AVA [12]) have commonly served as either source or target task. Among currently available video datasets, Kinetics has most commonly been used for TL.

An important question in TL is how transferable ImageNet and Kinetics are to other vision tasks. In particular, for ImageNet, multiple pieces of research have studied factors that influence its transferability to other similar image tasks [53, 38, 54]. In the video domain, most works on transferability have focused on HAR to HAR settings [18, 47, 13] and there has been very little research on the transferability from HAR to other video tasks that occur in different settings [25, 41]. For instance, the multi-label movie trailer genre classification (MTGC) is a video task of very distinct nature and content in which transferability has barely been studied. This task is difficult because genres do not have a specific physical expression in a frame or a sequence of frames. Consequently, genres must be inferred from characters, scenes, themes, dynamics, relationships and other abstract elements. In addition, the task implies a natural subjectivity: different human observers can assign different genres to the same trailer. In contrast to HAR clips, trailer settings are more diverse; namely, the story is usually not presented linearly, fictional elements may be included (e.g., characters, landscapes, devices, laws of physics, etc.) and the duration is generally longer.

In this paper, we present a general architecture called Dual Image and Video Transformer Architecture (DIViTA) for MTGC that enables exploiting both pretrained spatial and spatio-temporal visual backbones in a unified way. We empirically study different aspects that influence transferability from ImageNet and Kinetics to MTGC using a novel video movie trailer dataset. This paper makes the following contributions:

1. It introduces Trailers12k, a novel video movie trailer dataset composed of 12,000 trailers multi-labeled with ten different genres. As opposed to other existing trailer datasets, in Trailers12k each URL was manually verified and corrected both in terms of title-trailer agreement and video quality. In addition to metadata, frame-level and clip-level representations obtained with pretrained models on ImageNet and/or Kinetics are provided.

2. It proposes DIViTA, which is an MTGC architecture that leverages representations learned from ImageNet and/or Kinetics. DIViTA improves transferability by performing a straightforward adaptation stage that segments the input trailer based on shot transitions. Segmented representations are further aggregated with a transformer-based module to generate a trailer-level representation, which is used for genre classification.

3. It provides an extensive empirical evaluation of the transferability of convolutional and transformer backbones pretrained on ImageNet and/or Kinetics to Trailers12k MTGC. The impact of the segmentation strategy, frame rate, input video extension and spatio-temporal modeling strategy on classification performance are also studied. In addition, the use of lightweight architectures as an alternative to popular heavier architectures is explored.

This paper is organized as follows. Section 2 reviews related work on transferability from ImageNet and Kinetics, as well as works on MTGC using neural networks. Section 3 introduces the Trailers12k dataset, as well as its collection procedure and characteristics. Section 4 discusses important data and task dissimilarities between ImageNet, Kinetics, and Trailers12k. A general overview of the proposed multi-label genre classification architecture DIViTA is presented in Section 5 and Section 6 describes the experimental setting and evaluation methodology. Results are
discussed in terms of the transferability from ImageNet and/or Kinetics to Trailers12k MTGC in Section 7. Finally, the conclusions and perspectives for future work are presented in Section 8.

2. Related Work

This section reviews related works on transfer learning from ImageNet and Kinetics to image and video analysis tasks. It also describes MTGC methods, focusing on those using pretrained deep networks and trailer-centric datasets used in these works.

2.1. Transfer Learning from ImageNet and Kinetics

ImageNet pretraining has been a widespread practice for image classification [46, 21], object detection [11, 35], and object segmentation models [11, 28]. Transfer learning from ImageNet has been successfully applied not only to generalist classification datasets, but also to fine-grained (birds [46], flowers [21], etc.) and even to domain-specific datasets (chest X-rays [51, 20], skin lesions [29, etc.). Surprisingly, some of the latter datasets exhibit very different image distribution attributes and classification formulation than ImageNet.

Multiple studies have focused on the transferability of the representations learned from on ImageNet. For instance, Sharif Razavian et al. [38] compared the performance of pretrained deep networks with frozen feature extractors against hand-crafted feature algorithms on several image tasks. Another work [53] analyzed the degree of layer specialization at different points in deep networks with respect to transferability. Similarly, Kornblith et al. [23] analyzed the performance of several architectures and how it relates to transferability. For generalist image datasets, Zamir et al. [54] proposed the use of transferability between tasks as a framework to characterize their affinity.

ImageNet has also been widely used to initialize deep video architectures. For instance, Carreira and Zisserman [5] introduced I3D, a 2D ConvNet pretrained on ImageNet that is converted into a 3D video architecture by inflating (copying) trained filters along the temporal dimension. They showed that initializing I3D with ImageNet widely outperforms random parameter initialization for Kinetics as a target dataset. Other ConvNet architectures have followed I3D’s pretraining approach to improve the state of the art on several HAR datasets [13, 7]. More recently, pretraining on ImageNet has enabled the introduction of transformer architectures [1, 27] for video tasks.

Similarly, the transferability of Kinetics to other popular action recognition datasets has been studied directly [13] or indirectly to benchmark architectures [47, 13]. Kinetics pretraining has also been applied to other action recognition settings, such as egocentric actions [33], action recognition from drones [9] or actions in the dark [52]. Other studies have used Kinetics to initialize models for more distant video tasks, including sign language recognition [25] or autonomous vehicle decision-making [31].

2.2. Trailer Genre Classification

The task of genre recognition from video trailers has been studied over the past couple of decades. The first approaches to tackle this problem were based on features produced by handcrafted image algorithms that were validated on trailer datasets on the order of hundreds of videos [34, 55, 17]. More recently, multiple studies have leveraged deep neural networks for genre recognition on movie trailers with datasets of increasing sizes. For example, Simões et al. [40] proposed the use of a VGG-like architecture to first independently classify frames and later use aggregation strategies to obtain a global trailer prediction. To evaluate this approach, Simões...
et al. [40] introduce a dataset called LMTD comprised of 3,500 trailers with four different genres. In a follow-up work, Wehrmann and Barros [50] proposed a method that leverages a ResNet architecture pretrained on ImageNet and Places-360 to obtain frame-level representations that were aggregated with the CTT module, a Conv1D block that classifies the whole trailer. On the other hand, Cascante-Bonilla et al. [6] proposed a multi-modal method that exploits video, audio, poster, text, and metadata modalities. This method produces a sequence of representations per modality which is aggregated with a fastText-based module. For the video modality, the sequence of representations corresponds to frame-level representations generated by a VGG-16 network pretrained on ImageNet. The trailer global representation is obtained with an attention module that fuses different modal representations. This method was evaluated with the Movieescope dataset, which is composed of 5,027 trailer videos, text plots, and multiple metadata. Rodríguez Bribiesca et al. [36] extended the architecture by Cascante-Bonilla et al. [6], replacing the fastText-based multi-modal fusion with a transformer module, which improves the performance for the genre recognition task. Genre classification for whole movies has recently been enabled by the introduction of MovieNet [16], a dataset for holistic movie understanding that includes complete movies, subtitles, trailers, synopsis, metadata, etc. This dataset provides several tasks such as genre classification, action recognition, or cinematic style classification. While MovieNet includes trailers, they are not considered the main data and roughly half of the trailers do not have a one-to-one relationship with movies because several movies have more than one trailer.

3. Trailers12k Dataset

Trailers12k is a novel movie trailer dataset containing 12,000 titles, each associated with a YouTube video trailer, as well as poster and metadata gathered from IMDb. The collected information for a sample trailer is illustrated in Fig. 1. Table 1 compares data provided by Trailers12k with other similar movie trailer datasets used in previous works. As can be noted, Trailers12k is the second dataset with more samples and the only one in which both title-trailer correspondence and video quality are manually verified. Moreover, in addition to frame-level spatial representations, it provides clip-level spatio-temporal representations obtained with models pretrained on Kinetics and ImageNet-Kinetics. The overall compilation procedure can be outlined as follows:

1. A list of movie titles released between 2000 and 2019 with the top IMDb user rating was retrieved automatically.
2. For each movie, an automated YouTube search was performed using the title, appending the year and the word “trailer”. The top video result was downloaded.
3. Titles were filtered to keep only those having at least one of the top 10 most popular IMDb genres and at least 500 user votes.
4. Since in many cases the resulting trailer did not correspond to the title (it could be a remake, homonym, fan-made trailer, etc.), the trailers were manually curated. Specifically, we manually verified the correspondence of each title-trailer pair and replaced incorrect trailers with the best available on YouTube. We also replaced trailers in order to fulfill the

---

1 YouTube: [https://www.youtube.com/](https://www.youtube.com/)
2 Internet Movie Database: [https://www.imdb.com/](https://www.imdb.com/)
Figure 1: Trailers12k is a high-quality movie trailer dataset comprised of 12,000 titles. It publicly provides metadata, URLs, frame-level and clip-level trailer representations, poster representations, and MTGC evaluation splits.

Following video quality requirements: its duration must be between 60 and 210 seconds, its resolution must be at least 480p, and it should contain the least possible advertising and spatial/temporal padding (color bars/frames).

In Trailers12k, each title-trailer pair has one or more associated genres, which are indicators of the movie content commonly influencing audience decisions. In this sense, the dataset is multi-labeled with the top ten most popular IMDb genres: action, adventure, comedy, crime, drama, fantasy, horror, romance, science-fiction, and thriller. Fig. 2 shows the number of examples per genre in the dataset (blue bars). A strong genre imbalance can be observed: the most frequent genre (drama) occurs approximately four times more often than the less frequent one (science-fiction).

Table 1: Comparison of Trailers12k to other movie trailer datasets. Columns marked with ✓ indicate that data was publicly available to download during the preparation of this table (September 2022). The ImageNet/Kinetics column indicates representations extracted with pretrained models on the dataset.

| Dataset        | Samples | Manual Verification | Genres | Trailer URL | Poster URL | Plot | Metadata |
|----------------|---------|---------------------|--------|-------------|------------|------|----------|
| Zhou et al. [55] | 1,239   |                      | 4      | ✓           | ✓          | ✓    | ✓        |
| LMTD [50]       | 3,500   |                     | 4      | ✓           | ✓          | ✓    | ✓        |
| MovieScope [6]  | 5,027   | 13                  | ✓      | ✓           | ✓          | ✓    | ✓        |
| MovieNet [16]   | 32,753* | 28                  | ✓      | ✓           | ✓          | ✓    | ✓        |
| Trailers12K     | 12,000  | ✓                    | 10     | ✓           | ✓          | ✓    | ✓        |

*MovieNet authors mention 60k trailers in their paper, but only around 33k URLs are provided.
Figure 2: Comparison of the genre distribution in the complete dataset against the distribution in the subsets of the first split. The percentages and sample counts on top of the bars of each genre correspond to the complete dataset (blue).

The correlation between genres influences other aspects of genre distribution. To shed light on this, Fig. 3 (a) shows the histogram of the number of labels. Note that nearly 70% of the examples have 2 or 3 labels. In this sense, the dataset has a label cardinality and density of 2.5 and 0.25, respectively [48]. Similarly, Fig. 3 (b) shows a chord correlation diagram between genres. As expected, certain genre pairs like drama-thriller or comedy-romance are quite common, while movies labeled crime-fantasy or adventure-horror are rare.

In addition, each movie title includes metadata gathered from IMDb, such as release date, user rating, number of user votes, countries of origin, languages, plots, synopses, etc. There are 128 producing countries, although 85% of the movies were produced by the top 15 countries, as shown in Fig. 4 (a). From a total of 200 spoken languages, 86.1% of the titles use one of the 15 top languages in Fig. 4 (b). As can be seen, USA, UK, and Canada produced 53.3% of the movies, which explains why English is used in 51.1% of the titles. Fig. 4 (c) illustrates the increasing tendency of movie releases over the years. Each video trailer has a duration ranging from 30 to 210 seconds, following the distribution in Fig. 4 (d). Note that 87.9% of the trailers have a duration of less than 150 seconds, which corresponds to common industry trailer-making practices [32]. All trailers are normalized to 24 frames per second; in total, Trailers12k contains 407.61 hours of video represented by 35,217,616 frames.

As aforementioned, the dataset distribution is influenced by genre imbalance and correlation, which can make model evaluation challenging. To mitigate this difficulty, we provide three different dataset splits, following HMDB [24] and UCF101 [43] 3-fold evaluation strategies. Each split is composed of three subsets, namely training (70%), validation (10%), and test (20%). To generate the subsets, we used the SOIS [45] stratified partition algorithm for multi-label datasets. This ensures that the generated subsets follow the global genre distribution, as in Fig. 2 for the first split. The other two generated splits follow the global distribution in approximately the same way.

Trailers12k YouTube URLs of the trailers, IMDb URLs of the posters, metadata, frame-level and clip-level trailer representations extracted as described in Section 5 poster representations.
Figure 3: Genre distribution: (a) histogram of the number of labels and (b) correlation between genre pairs.

and evaluation splits are all publicly available at the dataset website\footnote{https://richardtml.github.io/Trailers12k} as well as in Zenode\footnote{https://doi.org/10.5281/zenodo.5716409}.

4. Dissimilarities between ImageNet/Kinetics and Trailers12k

The standard approach to perform transfer learning with neural networks can be generally divided into three steps. First, a model is pretrained on a source dataset. Second, a new architecture is adapted for the target task which reuses part of the pretrained model. For target classification tasks, this adaptation step commonly consists of removing specific layers related to the source task (last layers) and replacing them with layers suited for the target task. Finally, the new architecture is trained on the target dataset. It has been shown that the performance on the target task is influenced by factors like dataset size\cite{21,42,8}, domain variability\cite{8}, the capacity of the architecture to learn general representations\cite{46}, and the similarity between source and target datasets. Multiple works\cite{53,38,54} have studied transfer learning for different image analysis tasks and have consistently found that a greater similarity between the source and the target tasks results in better transferability, yielding a higher performance on the target task. In general, a positive transfer occurs when transfer learning benefits the performance on the target task compared with random initialization. Conversely, if the performance worsens when using transfer learning, it is referred to as negative transfer\cite{57}.

In this paper, we revisit the second step of the transfer learning process and propose a simple adaptation procedure that promotes positive transfer for movie trailer classification. To understand this procedure, called Snippet Generation stage, let’s first analyze important dissimilarities between target and source tasks. Although a trailer can be seen as a sequence of correlated images, its content and structure significantly differ from ImageNet images and Kinetics videos, as illustrated in Fig. 5. In particular, we focus on the following dissimilarities:
(a) **Spatial Content**: It is common for a movie trailer to present fictional elements (e.g., characters, objects, scenes, etc.), actions or dynamics (e.g., violating physical laws) that are not present in ImageNet real-world images or Kinetics human action clips.

(b) **Video Structure**: Since trailers are summaries generated from movies, their spatio-temporal structure is much more complex than HAR clips. Movies use a complex composition for storytelling [3]. The most elemental unit is the frame, a still image. A shot is a succession of frames without a camera cut. Generally, a shot has a single background focused on characters or objects that appear in the majority of frames, may be exhibiting some kind of dynamics (e.g., two people hugging). Commonly, a shot lasts from a fraction of a second to a few seconds. Moving up in the film composition, a scene is used to present a narration block through a series of shots with continuity of location, characters, and time. This normally is a few seconds long, but can last up to a few minutes. The filmmaking process has higher compositions, like sequences and acts, but they are used only for movie storytelling. As summaries aimed at capturing audience attention over a short period of time, trailers make use mainly of shots and scenes selected from the whole movie. Generally, the chosen shots and scenes are arranged in a sequence that does not usually correspond to the temporal order of the movie. The complex composition used by trailers differs considerably from
HAR clips that are composed of a few frames focused on humans performing an action.

(c) **Duration:** Trailer12k videos have an average duration ($\approx 122s$) that exceeds by one order of magnitude the duration of Kinetics-400 clips (10s) \[19\]. For video data analysis, this implies capturing more and longer term temporal information and more computing resources needed for processing.

The Snippet Generation stage aims to improve transfer learning by reducing dissimilarities (b) and (c). This procedure is described in detail in Section 5.

### 5. DIViTA Classification Architecture

The proposed classification architecture DIViTA has two general stages, namely Snippet Generation and Snippet Classification, as illustrated in Fig. 6. Roughly speaking, the Snippet Generation stage extracts from the input trailer a short video snippet composed of a sequence of clips, where each clip is preprocessed to become a more suitable input for the pretrained backbone. The Snippet Classification stage takes the extracted trailer snippet as input, generates a snippet representation by aggregating spatial/spatio-temporal clip-level representations, and classifies the trailer using this representation.

More specifically, the Snippet Generation stage takes an input trailer with $l$ frames and extracts a snippet $S$ with $c$ clips, each with $f$ frames. This preprocessing stage is carried out in four steps. First, a shot detection algorithm partitions the input trailer into a sequence of $m$ shots $(Z_1, \ldots, Z_m)$, which are short video segments of variable length demarcated by detected transitions (black frames, cuts, fades, etc.). This step aims to approximate the concept of movie shot used during the trailer production process, as described in Section 4. In the second step, each shot $Z_i$ is partitioned into smaller segments called trailer clips $Z'_i = (C_1, \ldots, C_{n_i})$, where the first $n_i - 1$ clips have $f$ frames. For the last clip $C_{n_i}$, if it is smaller than $f$ frames, then it is right
Figure 6: Overview of DIViTA’s processing steps.

padded with black frames up to \( f \). At this point, the trailer has been transformed into a sequence composed of the clips \( T = (C_{11}, \ldots, C_{n1}, \ldots, C_{1m}, \ldots, C_{nm}) \) of all shots. In the third step, a snippet sampling is performed by selecting \( c \) adjacent clips from \( T \) to form a trailer snippet \( S \). Note that these steps generate a video snippet with a high correlation at two different levels, at a lower (inter-frame) level since the frames of a clip belong to the same detected shot, and at a higher (inter-clip) level because all the clips of a snippet are adjacent. In the last step, which is only performed for a 2D Backbone, each clip \( C_j \in S \) is represented by selecting a single frame out of the \( f \) frames.

On the other hand, the Snippet Classification stage is a deep neural network architecture that classifies the preprocessed trailer snippet, and consists of three modules: a 2D/3D Backbone to obtain spatio-temporal representations of trailer clips, a transformer-based module to aggregate spatio-temporal information and a linear layer (CLS) for classification. The 2D/3D Backbone generates a representation vector \( r_j \in \mathbb{R}^b \) for each of the snippet’s clip \( C_j \) of the snippet, where \( b \) is the backbone output size. This module is constructed by transferring the representation extraction layers of a classification architecture pretrained on ImageNet and/or Kinetics. In the case of an image 2D Backbone, \( C_j \) is a single frame, so \( r_j \) encodes purely spatial information. In contrast, for a video 3D Backbone, since \( C_j \) is a sequence of frames, \( r_j \) encodes spatio-temporal information. In either case, the output is a sequence of clip representations \( (r_1, \ldots, r_c) \), which is combined by the Clip Aggregation Transformer into a single vector \( s \in \mathbb{R}^d \) with spatio-temporal information at the snippet level. The architecture of the Clip Aggregation Transformer is illustrated in Fig. 7. This architecture is based on the original Transformer by Vaswani et al. [49], but incorporates an additional Position-wise Fully Connected Layer at the beginning to reduce each input clip representation \( r_j \) to a vector of size \( d < b \). The intuition behind adding the latter layer is that it can reduce parameter explosion in the following layers and thus helps mitigate overfitting. The next four blocks in the Clip Aggregation Transformer produce a new sequence of clip representations that is intended to capture dependencies among clip representations. The Average Pooling layer at the end is applied over the time dimension to aggregate the sequence into a single representation vector \( s \) for the whole snippet. Finally, CLS is a fully connected layer
Figure 7: Clip Aggregation Transformer module based on [49]. At the beginning of the module, a Position-wise Fully Connected Layer is incorporated to decrease the size of clip-level vectors.

followed by a sigmoid activation function that classifies s, producing a vector p of size g where each element represents the probability that the snippet belongs to a given genre.

DIViTA has two operation modes. At training time, a single snippet S is used to classify the input trailer. In the third step of the Snippet Generation, a trailer snippet S composed of c adjacent clips is selected by picking a starting position from $[1, |T| - c]$ uniformly at random. This snippet’s probability vector p is considered to be the classification for the complete trailer. Since different snippets can be generated from different starting positions, this strategy provides an implicit temporal augmentation effect and at the same time lowers the computational requirements during training. At inference time, all the snippets $(S_1, \ldots, S_q)$ are used to classify the input trailer. In the third step of the Snippet Generation, the trailer clip sequence T is partitioned into a sequence of snippets $(S_1, \ldots, S_q)$. In inference mode, the classification for the complete trailer is obtained by genre-wise averaging the probability vectors $(p_1, \ldots, p_q)$ of all the snippets.

6. Experimental Setup

For the empirical evaluation, we fix some training and model hyperparameters while studying the impact of other hyperparameters in terms of different performance metrics. We also compare the performance of our models with baselines. Below, we detail our experimental setup. The code to reproduce our main results is publicly available.

Training. All models are trained for 100 epochs in batches of 32 examples. We adopt the binary cross entropy loss and early stopping based on the validation set loss. We use the ADAM optimizer with an initial learning rate of $1e^{-4}$ which is decreased by a factor of 10 every time the validation loss plateaued for 20 epochs. Backbone weights are frozen to reduce computing and time resources. For all experiments, we use a DGX A100 Server.

Unless stated otherwise for a particular experiment, the default configuration for the Snippet Generation stage is set to 30 clips per snippet, each of which is composed of 24 frames taken from the output of the shot detector (Shot-24). The Snippet Classification stage uses a Swin-2D pretrained on ImageNet-1K or a Swin-3D backbone pretrained on ImageNet-1K and Kinetics-400. The Clip Aggregation Transformer has 4 heads with linear projections of 128 dimensions.
Evaluation. We choose four metrics based on the area under the precision-recall curve commonly used in multi-label movie classification works \[50, 6\]. $\mu AP$ (micro average) is computed using all labels as a single binary classification task. This metric provides global information regarding the predictions, allowing more frequent classes to have a greater impact on performance. In the $m AP$ (macro average) metric, an AUC is computed per class and the results are averaged. This provides performance information regarding the classes independent of their frequency. $w AP$ (weighted average) is similar to the $m AP$ metric, but the average is weighted by the frequency of the class. In contrast to $m AP$, $w AP$ takes into account genre frequency. Finally, $s AP$ (sample average) computes an AUC per example and the results are averaged. All the models are trained and evaluated on each of the three Trailers12k splits; the mean and standard deviation taken over the three test sets are reported for each metric.

Baselines. In order to study the impact of different parts of DIViTA, we perform a straightforward ablation study by replacing key components with simpler alternatives. In addition, we compare DIViTA with the CTT-MMC-A architecture proposed by Wehrmann and Barros \[50\] for multi-label genre trailer classification using only information about the frames (unimodal). Since the original training dataset and source code for CTT-MMC-A \[50\] are not publicly available, we reproduce the architecture as faithfully as possible from the paper description and train it on the Trailers12k dataset. However, for a fair comparison, we use a ResNet backbone pretrained only on ImageNet and omit the additional pretraining on Places360. We call the resulting model CTT-MMC-A$^\dagger$.

7. Results and Discussion

We evaluate the impact of the clip generation strategy and the clip frame rate on the transferability of ImageNet and/or Kinetics representations. We analyze Convolutional and Transformer backbones, pretrained on ImageNet and/or Kinetics, comparing both performance and computational requirements. We also study different snippet lengths and snippet aggregation strategies.

7.1. Shot Partitioning

The first two steps in the Snippet Generation stage are aimed at reducing dissimilarities between images/human action clips and movie shots. This is achieved by first segmenting the input trailer into shots of variable length, and then partitioning each shot into clips with an fixed number of frames ($f$). To segment trailers into shots, we use the shot detection network TransNet V2 \[44\]. Fig. 8 shows the histogram of the number of frames per shot for Trailers12k obtained by TransNet V2.

Clip length $f$ determines the amount of information provided to the backbone, which may impact transferability. This is particularly important for Kinetics representations because they are computed with all the clip’s $f$ frames. We explore configurations with $f = 24$ and $f = 32$ clip lengths, called Shot-24 and Shot-32, which correspond respectively to the mode and mean of the distribution of shot durations observed in Fig. 8. To ascertain the benefits of the proposed strategy to generate clips based on shot partitioning, we compare it with a simpler segmentation strategy. In Seq-24 and Seq-32 configurations, clips are generated by simply taking contiguous sequences of 24 and 32 frames from the trailer. Fig. 9 illustrates an example of clip generation with Seq-24 and Shot-24 configurations.

Table 2 reports results comparing both clip generation strategies Seq-$f$ and Shot-$f$ using ImageNet and ImageNet-Kinetics backbones. As can be observed, the Shot-$f$ strategy improves
Figure 8: Histogram of shot durations for the Trailers12k obtained with TransNet V2 [44].

Figure 9: Comparison of clip generation with Seq-24 (blue) and Shot-24 (pink). In the middle, content frames are represented as solid grey rectangles, while transition frames as empty rectangles. In Seq-24, clips are constituted by sequential frames, including both content and transition frames. In Shot-24, clips are made up of sequential content frames only, omitting transition frames.

transferability, especially for the ImageNet-Kinetics backbone. More specifically, the highest performance is obtained in all the metrics by Shot-24 using an ImageNet-Kinetics backbone; for instance, it achieves an average $\mu AP$ of 75.57, which is 3.75 and 4.1 points higher than Seq-24 and Seq-32, respectively. Standard deviations are also generally lower for ImageNet-Kinetics backbones with the Shot-f strategy. This could be an effect of the shot detector, which helps generate clips in which the majority of frames are highly correlated, thus reducing the risk of having transition frames within the clips. This is particularly important since an ImageNet-Kinetics backbone consumes all the frames of a clip to generate its representation. For configurations using the ImageNet backbone, the gains are lower; for instance, the Shot-24 $\mu AP$ is around 1.83 points higher than Seq-24. This can be explained by the fact that a 2D Backbone takes as input a single frame from the clip, selected using on color histogram similarity to the clip’s average color histogram, which reduces the probability of taking a transition frame. For ImageNet-Kinetics, Shot-24 slightly outperforms Shot-32 in all the metrics. Note that because Shot-24 produces shorter clips, the number of training samples is also 31% larger than Shot-32.
Table 2: Performance comparison of clip generation strategies Seq-\( f \) and Shot-\( f \) in DIViTA.

| Clip Generation | Metrics \( \uparrow \) |
|------------------|----------------------|
|                  | \( \mu AP \) | \( m AP \) | \( w AP \) | \( s AP \) |
| **ImageNet**     |            |      |      |        |
| Seq-24           | 70.83±1.93 | 66.39±1.86 | 70.29±1.03 | 76.04±1.83 |
| Seq-32           | 70.13±2.03 | 66.31±2.12 | 70.13±2.05 | 75.95±2.04 |
| Shot-24          | 72.66±1.37 | 67.68±1.36 | 71.76±1.09 | 77.49±1.18 |
| Shot-32          | 72.90±1.20 | 67.77±1.58 | 71.70±1.10 | 77.45±1.11 |
| **ImageNet-Kinetics** |        |      |      |        |
| Seq-24           | 71.82±1.33 | 66.55±1.24 | 69.88±1.61 | 76.01±1.24 |
| Seq-32           | 71.42±1.09 | 66.89±1.30 | 69.93±2.04 | 75.94±1.72 |
| Shot-24          | **75.57±0.66** | **70.48±0.41** | **74.21±0.40** | **80.02±0.47** |
| Shot-32          | 75.21±0.43 | 69.64±0.48 | 73.32±0.31 | 79.16±0.29 |

Table 3: Gradual increase of number of frames per clip in DIViTA.

| Frame Rate | Metrics \( \uparrow \) |
|------------|----------------------|
|            | \( \mu AP \) | \( m AP \) | \( w AP \) | \( s AP \) |
| **ImageNet-Kinetics** |        |      |      |        |
| 4          | 72.55±0.89 | 67.50±0.91 | 71.43±0.86 | 77.40±0.79 |
| 6          | 72.93±0.60 | 67.80±0.68 | 71.73±0.71 | 77.89±0.50 |
| 8          | 73.04±0.55 | 67.95±0.60 | 71.86±0.57 | 78.24±0.66 |
| 12         | 73.34±0.77 | 68.07±0.73 | 71.96±0.39 | 78.63±0.49 |
| 24         | **75.57±0.66** | **70.48±0.41** | **74.21±0.40** | **80.02±0.47** |

7.2. Frame Rate

Movement can be an important clue for video analysis tasks. For human action clips, the main source of movement comes from humans performing an action and its extent depends on the type of action. In contrast, in a movie trailer, characters, objects, background or events can independently exhibit great variability in the amount of movement, which also depends on the genre [55]. To explore how this aspect impacts transferability, we reduce the frame rate of Trailers12k videos to increase the amount of apparent movement. The downsampling procedure simply selects frames at equal intervals, e.g., to produce an 8 FPS video only the first out of each three consecutive frames is kept. Table 3 reports results at different frame rates. As we can observe, performance increases as FPS increases, reaching the top result for all the metrics at the original 24 FPS. Nevertheless, lower frame rates achieve competitive results at a fraction of the computational cost of the top model. For instance, 4 FPS decreases \( \mu AP \) 3.02 points using only \( \frac{1}{6} \) of memory to represent the input tensor. This can be useful to deploy models with limited computational resources.

7.3. Spatio-Temporal Extension

DIViTA makes use of snippets to loosely approximate movie scenes and use them as shortened representations for the whole trailer. This simplifies the batch-based training process, implicitly
Table 4: Gradual increase of the spatio-temporal receptive field in DIViTA.

| Clips Per Snippet | Metrics † | µAP          | mA            | wA            | sA            |
|-------------------|-----------|--------------|---------------|---------------|---------------|
|                   | ImageNet-Kinetics |               |               |               |               |
| 5                 | 72.86±0.69 | 68.78±0.56   | 72.90±0.92    | 77.16±0.98    |
| 10                | 74.93±0.77 | 70.25±0.67   | 74.14±1.04    | 79.12±0.38    |
| 15                | 75.17±0.69 | 70.36±0.52   | 74.02±0.68    | 79.44±0.45    |
| 20                | 75.39±0.65 | 70.42±0.48   | 74.25±0.59    | 79.69±0.51    |
| 30                | 75.57±0.66 | 70.48±0.41   | 74.21±0.40    | 80.02±0.47    |
| 40                | 75.53±0.68 | 70.71±0.42   | 74.17±0.39    | 80.06±0.45    |
| 50                | 75.46±0.75 | 70.24±0.40   | 74.02±0.42    | 79.97±0.45    |
| 60                | 74.87±0.73 | 70.17±0.53   | 74.02±0.45    | 79.99±0.50    |

introduces a data augmentation mechanism, and decreases memory and processing requirements. However, reducing the number of clips per snippet also limits the spatio-temporal receptive field of the Clip Aggregation Transformer module. Given the weakly supervised labeling nature of Trailers12k genres, this could result in misleading predictions at the snippet level. Recall that a training snippet is generated by randomly sampling contiguous clips, assigning to it the genres of the whole trailer. Consequently, if the clips within the snippet do not contain information related to one of the assigned genres, the training process receives a misleading supervisory signal with respect to that genre. Increasing the number of clips per snippet (approximating the whole trailer) helps alleviate this issue at the cost of reducing the benefits of a shortened representation. Table 4 reports results of configurations with increasing spatio-temporal receptive fields. We observe that the best performance is obtained with snippets of 30 to 40 clips, outperforming even configurations with a larger number of clips. The performance loss with larger snippets could be a result of reducing the sampling space of snippets during the random selection process. Interestingly, 10 FPS is just 0.64 µAP points below the 30 FPS configuration using only \( \frac{1}{3} \) of the memory for the input tensor.

7.4. Spatio-Temporal Modeling

The Transformer Clip Aggregation module generates spatio-temporal representations at the snippet level. From the MTGC task point of view, this loosely captures relations at the trailer scene level. In order to assess this module’s ability to model spatio-temporal relations among clips, we compare it with convolutional and recurrent alternatives. The main advantage of a transformer architecture lies in the attention mechanism. This enables capturing relations between any pair of clips, regardless of their relative position within the snippet. In contrast, a convolutional approach can only find relations among clips within its receptive field determined by filter size. Similarly, a standard recurrent-based module is limited to model relations sequentially. We carry out a hyperparameter search to find the best configurations for the convolutional and recurrent modules, preserving those with approximately the same number of parameters. For the recurrent version, we use one GRU cell with 115 hidden units. On the other hand, the convolutional version uses one Conv1D layer with 128 filters of size 3, which is similar to the CTT-MMC-A† aggregation strategy, but with a different number of filters and filter sizes.

Table 5 reports results corresponding to the three modules. In all metrics, the Clip Aggregation Transformer module outperforms the convolutional and recurrent versions for both ImageNet and ImageNet-Kinetics backbones. In addition, standard deviations are consistently lower. This can
be explained by the attention mechanism’s ability to better capture the kind of temporal relations among shots that are common in a trailer, namely, two correlated shots can appear in arbitrary positions within the trailer.

7.5. ImageNet and Kinetics Transferability

We use DIViTA to study the degree of transferability from ImageNet and Kinetics to Trailers12k. We focus on three aspects: pretraining dataset, backbone architecture, and backbone computational requirements. In our experiments, we consider lightweight ConvNets (ShuffleNet-2D [30] and ShuffleNet-3D [22]); heavy ConvNets (ResNet [14] and ResNet2+1D [47]); and Vision Transformers (Swin-2D [26] and Swin-3D [27]). Table 6 summarizes the results from these experiments.

**ImageNet vs. Kinetics.** Convolutional backbones pretrained on ImageNet outperform those pretrained on Kinetics. This is in line with the intuition that it can be easier to predict genres from spatial elements (characters, objects, scenes, etc.) than from dynamic information (actions, motion, etc.). However, the difference in performance is only 0.54 $\mu$AP points for ResNet. From a pretraining point of view, this suggests that Kinetics clips (with spatio-temporal information but less spatially diverse) provide a different but competitive knowledge source to ImageNet images (more spatially rich, but purely static). Moreover, we investigate using two different approaches whether both pretraining tasks can be complementary or not. The first approach, called Fusion, uses a two-stream workflow inspired by [39]. Essentially, it has two identical processing pipelines: one for ImageNet and one for Kinetics, the prediction logits of which are averaged (late fusion). We observe that this approach improves the results with respect to a single pretraining by 0.97 $\mu$AP points for ShuffleNet and 1.86 for ResNet. In the second approach, the transformer backbone architecture Swin-3D is first pretrained on ImageNet and later on Kinetics, as described in [27]. This dual pretraining outperforms single ImageNet pretraining (Swin-2D) by 2.5 $\mu$AP points. These results suggest that ImageNet and Kinetics can provide complementary information as pretraining datasets, thus benefiting the transferability of learned representations to the MTGC task.

**ConvNets vs. Transformers.** We compare ResNet and ShuffleNet convolutional architectures to Swin transformer architectures. We observe that the Swin-3D transformer architecture outperforms convolutional backbones for both ImageNet and/or Kinetics, while having similar standard
Table 6: Performance comparison of backbone architectures and pretraining tasks. Percentages of number of parameters and FLOPS are computed with respect to Swin-3D (top performance).

| Backbone          | Pretraining | Metrics ↑ | Params ↓ | FLOPS ↓ |
|-------------------|-------------|-----------|----------|---------|
|                   |             | µAP       | mAP      | w/AP    | sAP     |
|                   |             | (M) %     | (G) %    |         |         |
| CTT-MMC-A† [50]   | ✓           | 69.27±2.87| 65.37±1.61| 68.93±2.09| 75.09±3.01|
| Light Conv        |             |           |          |         |         |
| ShuffleNet-2D     | ✓           | 71.14±0.68| 66.01±0.46| 70.17±0.44| 75.80±0.85| 1.7     | 6.09   | 4.3    | 0.27   |
| ShuffleNet-3D     | ✓           | 63.43±1.54| 58.18±1.50| 63.59±1.46| 69.49±1.58| 1.7     | 6.09   | 8.5    | 0.53   |
| ShuffleNet-Fusion | ✓ ✓         | 72.11±0.56| 67.08±0.37| 71.42±0.41| 76.66±0.73| 3.3     | 11.82  | 12.9   | 0.81   |
| Heavy Conv        |             |           |          |         |         |
| ResNet            | ✓           | 71.42±0.59| 66.63±0.36| 70.64±0.34| 76.41±0.38| 23.9    | 85.66  | 122.7  | 7.71   |
| ResNet-2+1D       | ✓           | 70.88±1.37| 64.99±1.37| 69.88±1.30| 75.15±1.08| 31.7    | 113.62 | 1823.4 | 114.67  |
| ResNet-Fusion     | ✓ ✓         | 73.28±0.66| 68.03±0.63| 72.14±0.72| 77.76±0.44| 55.6    | 199.28 | 1946.1 | 122.39  |
| Transformer       |             |           |          |         |         |
| Swin-2D           | ✓           | 72.66±1.37| 67.68±1.36| 71.76±1.09| 77.49±1.18| 27.9    | 100.00 | 114.0  | 7.16   |
| Swin-3D           | ✓ ✓         | 75.57±0.66| 70.48±0.41| 74.21±0.40| 80.02±0.47| 27.9    | 100.00 | 1590.0 | 100.00  |

deviations to the top performance of convolutional backbones. It is worth noting that Swin-3D achieves the top results using a standard pretraining approach for transformer-based video architectures, in contrast to the Fusion two-stream workflow. On the other hand, although Swin-2D has higher average performance than 2D ConvNets and ShuffleNet-Fusion, its standard deviation is also higher.

**Computational Requirements.** We analyze the trade-off between performance and computational requirements, as shown in Fig. 10. We observe that lightweight convolutional fusion (ShuffleNet-Fusion) has a performance 3.46 µAP lower than the top configuration (Swin-3D). Nevertheless, the number of parameters is one order of magnitude smaller and the number of FLOPS is two orders of magnitude smaller for ShuffleNet-Fusion. Therefore, ShuffleNet-Fusion offers an excellent trade-off between performance and computational requirements, which makes it appealing for environments with low computational resources, especially since convolutions have been optimized at both hardware and software levels for these environments [31].

### 8. Conclusions

In this paper, we study the transferability of representations learned from generalist image classification and video human action recognition datasets to multi-label movie trailer genre classification. Specifically, we collected a movie trailer dataset with manually verified title-trailer pairs, which we called Trailers12k, and performed an empirical study of transferability from ImageNet and Kinetics to such dataset. We also proposed DIViTA, a classification architecture that performs shot detection to segment the trailer into highly correlated clips, providing a more cohesive input for pretrained backbones. This reduces the gap between the spatio-temporal structure of the source and target datasets, thus improving the transferability of the learned representations.

Our results show that ImageNet and Kinetics representations are comparatively transferable to the MTGC task. Moreover, these representations provide complementary information that can be...
combined to improve classification performance. In fact, the highest classification performance is achieved with Transformer backbones that leverage both datasets to learn spatio-temporal representations. Nevertheless, competitive performance with much lower computational requirements can be achieved by separately pretraining dataset-specific ShuffleNets, a family of lightweight convolutional architectures. Similarly, the computational cost can be decreased by reducing the video frame rate and snippet size, greatly lowering the memory and processing requirements while maintaining competitive performance. Hence, such configurations are attractive for inference on low-resource environments. Interestingly, the performance obtained by ImageNet backbones representing clips with a single frame is higher than the performance of Kinetics models and is only slightly lower than ImageNet-Kinetics models, which require multiple frames per clip. This suggests that although MTGC is a video analysis task, solely using spatial information could be enough to achieve competitive models for the task. Recent works studying the importance of temporal information on video tasks have found similar results for certain action recognition classes [15] and video-language understanding tasks [4].

While this piece of research analyzed some factors influencing the transferability of learned representations from two popular computer vision datasets to genre trailer classification, its results have given rise to further questions that can be explored as future research. For instance, foundation models pretrain architectures on diverse datasets and data modalities, aiming to learn general representations that are transferable to a broader range of tasks. For genres that contain spatio-temporal information that differs from the representations learned on ImageNet and Kinetics (like fantasy or science-fiction), applying foundation models could be a promising approach to improve results. Finally, our results suggest that although MTGC could benefit from both ImageNet and Kinetics pretraining, competitive performance at a fraction of model complexity can be achieved using only spatial information. Therefore, another relevant future research direction is to design architectures and training methods that can model spatio-temporal dependencies more efficiently; e.g., models that simultaneously leverage ImageNet and Kinetics, privileging spatial information while, at the same time making a more efficient use of spatio-temporal information.
Acknowledgements

This work was supported by a PAPIIT grant [IA104016]. The first author has been supported by the National Council for Science and Technology (CONACYT), Mexico, scholarship number 326014. We acknowledge the high-performance computing (HPC) resources and services provided by the Corporación Ecuatoriana para el Desarrollo de la Investigación y la Academia (CEDIA).

References

[1] Anurag Arnab, Mostafa Dehghani, Georg Heigold, Chen Sun, Mario Lucic, and Cordelia Schmid. ViViT: A video vision Transformer. ArXiv, abs/2103.15691, 2021.

[2] Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. Enriching word vectors with subword information. Transactions of the Association for Computational Linguistics, 5, 07 2016. doi: 10.1162/tacl_a_00051.

[3] Leo Braudy. Film: An international history of the medium. Film Quarterly (ARCHIVE), page 59, 1995.

[4] Shyamal Buch, Cristóbal Eyzaguirre, Adrien Gaidon, Jiajun Wu, Li Fei-Fei, and Juan Carlos Niebles. Revisiting the “video” in video-language understanding. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2917–2927, 2022.

[5] João Carreira and Andrew Zisserman. Quo Vadis, action recognition? a new model and the Kinetics dataset. In 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 4724–4733, 2017. doi: 10.1109/CVPR.2017.502.

[6] Paola Cascante-Bonilla, Kalpathy Sitaraman, Mengjia Luo, and Vicente Ordonez. Movi-escape: Large-scale analysis of movies using multiple modalities. ArXiv, abs/1908.03180, 2019.

[7] Yunpeng Chen, Yannis Kalantidis, Jianshu Li, Shuicheng Yan, and Jiashi Feng. Multi-Fiber networks for video recognition. In Proceedings of the European Conference on Computer Vision (ECCV), pages 352–367, 2018.

[8] Mehdi Cherti and Jenia Jitsev. Effect of pre-training scale on intra- and inter-domain full and few-shot transfer learning for natural and medical X-ray chest images. arXiv preprint arXiv:2106.00116, 5, 2021.

[9] Jinwoo Choi, Gaurav Sharma, Samuel Schulte, and Jia-Bin Huang. Shuffle and attend: Video domain adaptation. In European Conference on Computer Vision, pages 678–695. Springer, 2020.

[10] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. ImageNet: A large-scale hierarchical image database. In 2009 IEEE Conference on Computer Vision and Pattern Recognition, pages 248–255. IEEE, 2009.

[11] R. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In 2014 IEEE Conference on Computer Vision and Pattern Recognition, pages 580–587, 2014.
[12] Chunhui Gu, Chen Sun, David A Ross, Carl Vondrick, Caroline Pantofaru, Yeqing Li, Sudheendra Vijayanarasimhan, George Toderici, Susanna Rico, Rahul Sukthankar, et al. AVA: A video dataset of spatio-temporally localized atomic visual actions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6047–6056, 2018.

[13] Kensho Hara, Hirokatsu Kataoka, and Yutaka Satoh. Can spatiotemporal 3D CNNs retrace the history of 2D CNNs and ImageNet? In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6546–6555, 2018.

[14] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 770–778, 2016.

[15] De-An Huang, Vignesh Ramanathan, Dhruv Mahajan, Lorenzo Torresani, Manohar Paluri, Li Fei-Fei, and Juan Carlos Niebles. What makes a video a video: Analyzing temporal information in video understanding models and datasets. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7366–7375, 2018.

[16] Qingqiu Huang, Yu Xiong, Anyi Rao, Jiaze Wang, and Dahua Lin. MovieNet: A holistic dataset for movie understanding. In The European Conference on Computer Vision (ECCV), 2020.

[17] Yin-Fu Huang and Shih-Hao Wang. Movie genre classification using SVM with audio and video features. In International Conference on Active Media Technology, pages 1–10. Springer, 2012.

[18] Hirokatsu Kataoka, Tenga Wakamiya, Kensho Hara, and Yutaka Satoh. Would mega-scale datasets further enhance spatiotemporal 3D CNNs? arXiv preprint arXiv:2004.04968, 2020.

[19] Will Kay, Joao Carreira, Karen Simonyan, Brian Zhang, Chloe Hillier, Sudheendra Vijayanarasimhan, Fabio Viola, Tim Green, Trevor Back, Paul Natsev, et al. The Kinetics human action video dataset. arXiv preprint arXiv:1705.06950, 2017.

[20] Alexander Ke, William Ellsworth, Oishi Banerjee, Andrew Y Ng, and Pranav Rajpurkar. CheXtransfer: Performance and parameter efficiency of ImageNet models for chest x-ray interpretation. In Proceedings of the Conference on Health, Inference, and Learning, pages 116–124, 2021.

[21] Alexander Kolesnikov, Lucas Beyer, Xiaohua Zhai, Joan Puigcerver, Jessica Yung, Sylvain Gelly, and Neil Houlsby. Big Transfer (BiT): General visual representation learning. In Andrea Vedaldi, Horst Bischof, Thomas Brox, and Jan-Michael Frahm, editors, Computer Vision – ECCV 2020, pages 491–507, Cham, 2020. Springer International Publishing.

[22] Okan Köpükülü, Neslihan Kose, Ahmet Gunduz, and Gerhard Rigoll. Resource efficient 3D convolutional neural networks. In 2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW), pages 1910–1919. IEEE, 2019.

[23] Simon Kornblith, Jonathon Shlens, and Quoc V Le. Do better ImageNet models transfer better? In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2661–2671, 2019.
[24] H. Kuehne, H. Jhuang, E. Garrote, T. Poggio, and T. Serre. HMDB: A large video database for human motion recognition. In Proceedings of the International Conference on Computer Vision (ICCV), 2011.

[25] Dongxu Li, Cristian Rodriguez, Xin Yu, and Hongdong Li. Word-level deep sign language recognition from video: A new large-scale dataset and methods comparison. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 1459–1469, 2020.

[26] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baoning Guo. Swin Transformer: Hierarchical vision transformer using shifted windows. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), 2021.

[27] Ze Liu, Jia Ning, Yue Cao, Yixuan Wei, Zheng Zhang, Stephen Lin, and Han Hu. Video Swin Transformer. arXiv preprint arXiv:2106.13230, 2021.

[28] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3431–3440, 2015.

[29] Adria Romero Lopez, Xavier Giro-i Nieto, Jack Burdick, and Oge Marques. Skin lesion classification from dermoscopic images using deep learning techniques. In 2017 13th Iasted International Conference on Biomedical Engineering (BioMed), pages 49–54. IEEE, 2017.

[30] Ningning Ma, Xiangyu Zhang, Hai-Tao Zheng, and Jian Sun. ShuffleNet V2: Practical Guidelines for Efficient CNN Architecture, pages 122–138. Springer International Publishing, 01 2018. ISBN 978-3-030-01263-2. doi: 10.1007/978-3-030-01264-9_8.

[31] Sparsh Mittal. A survey on optimized implementation of deep learning models on the NVIDIA Jetson platform. Journal of Systems Architecture, 97:428–442, 2019. ISSN 1383-7621. doi: https://doi.org/10.1016/j.sysarc.2019.01.011.

[32] Peter J Pepe and Joseph W Zarzynski. Documentary Filmmaking for Archaeologists. Routledge, 2016.

[33] Chiara Plizzari, Mirco Planamente, Gabriele Goletto, Marco Cannici, Emanuele Gusso, Matteo Matteucci, and Barbara Caputo. E2 (GO) MOTION: Motion augmented event stream for egocentric action recognition. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 19935–19947, 2022.

[34] Zeeshan Rasheed, Yaser Sheikh, and Mubarak Shah. On the use of computable features for film classification. IEEE Transactions on Circuits and Systems for Video Technology, 15(1):52–64, 2005.

[35] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You Only Look Once: Unified, real-time object detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 779–788, 2016.

[36] Isaac Rodríguez Bribiesca, Adrián Pastor López Monroy, and Manuel Montes-y Gómez. Multimodal weighted fusion of Transformers for movie genre classification. In Proceedings of the Third Workshop on Multimodal Artificial Intelligence, pages 1–5, Mexico City,
[37] Michael T. Rosenstein, Zvika Marx, Leslie Pack Kaelbling, and Thomas G. Dietterich. To transfer or not to transfer. In *NIPS’05 Workshop, Inductive Transfer: 10 Years Later*, 2005.

[38] Ali Sharif Razavian, Hossein Azizpour, Josephine Sullivan, and Stefan Carlsson. CNN features off-the-shelf: an astounding baseline for recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 806–813, 2014.

[39] Karen Simonyan and Andrew Zisserman. Two-stream convolutional networks for action recognition in videos. In *Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 1*, NIPS’14, page 568–576, Cambridge, MA, USA, 2014. MIT Press.

[40] Gabriel Simões, Jónatas Wehrmann, Rodrigo Barros, and Duncan Ruiz. Movie genre classification with convolutional neural networks. In *2016 International Joint Conference on Neural Networks (IJCNN)*, pages 259–266, 07 2016. doi: 10.1109/IJCNN.2016.7727207.

[41] Gurkirt Singh, Stephen Akrigg, Manuele Di Maio, Valentina Fontana, Reza Javanmard Alitappeh, Suman Saha, Kossar Jeddisaravi, Farzad Yousefi, Jacob Culley, Tom Nicholson, et al. ROAD: The ROad event awareness dataset for autonomous driving. *arXiv preprint arXiv:2102.11585*, 2021.

[42] Deepak Soekhoe, Peter van der Putten, and Aske Plaat. On the impact of data set size in transfer learning using deep neural networks. In Henrik Boström, Arno Knobbe, Carlos Soares, and Panagiotis Papapetrou, editors, *Advances in Intelligent Data Analysis XV*, pages 50–60, Cham, 2016. Springer International Publishing.

[43] Khurram Soomro, Amir Roshan Zamir, and Mubarak Shah. UCF101: A dataset of 101 human actions classes from videos in the wild. *arXiv preprint arXiv:1212.0402*, 2012.

[44] Tomáš Souček and Jakub Lokoč. TransNet V2: An effective deep network architecture for fast shot transition detection. *arXiv preprint arXiv:2008.04838*, 2020.

[45] Piotr Szymański and Tomasz Kajdanowicz. A network perspective on stratification of multi-label data. In Luis Torgo, Bartosz Krawczyk, Paula Branco, and Nuno Montiz, editors, *Proceedings of the First International Workshop on Learning with Imbalanced Domains: Theory and Applications*, volume 74 of *Proceedings of Machine Learning Research*, pages 22–35, ECML-PKDD, Skopje, Macedonia, 2017. PMLR.

[46] Mingxing Tan and Quoc Le. EfficientNet: Rethinking model scaling for convolutional neural networks. In *International Conference on Machine Learning*, pages 6105–6114. PMLR, 2019.

[47] Du Tran, Heng Wang, Lorenzo Torresani, Jamie Ray, Yann LeCun, and Manohar Paluri. A closer look at spatiotemporal convolutions for action recognition. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6450–6459, 06 2018. doi: 10.1109/CVPR.2018.00675.
[48] Grigorios Tsoumakas, Ioannis Katakis, and Ioannis Vlahavas. *Mining Multi-label Data*, pages 667–685. Springer US, 2010. ISBN 978-0-387-09823-4. doi: 10.1007/978-0-387-09823-4_34.

[49] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS’17, page 6000–6010, Red Hook, NY, USA, 2017. Curran Associates Inc. ISBN 9781510860964.

[50] Jônatas Wehrmann and Rodrigo C. Barros. Movie genre classification: A multi-label approach based on convolutions through time. *Applied Soft Computing*, 61:973–982, 2017. ISSN 1568-4946. doi: https://doi.org/10.1016/j.asoc.2017.08.029.

[51] Yiting Xie and David Richmond. Pre-training on grayscale ImageNet improves medical image classification. In *Proceedings of the European Conference on Computer Vision (ECCV) Workshops*, pages 476–484, 2018.

[52] Yuecong Xu, Jianfei Yang, Haozhi Cao, Kezhi Mao, Jianxiong Yin, and Simon See. ARID: A new dataset for recognizing action in the dark. In *International Workshop on Deep Learning for Human Activity Recognition*, pages 70–84. Springer, 2021.

[53] Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson. How transferable are features in deep neural networks? In Z. Ghahramani, M. Welling, C. Cortes, N. Lawrence, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems*, volume 27. Curran Associates, Inc., 2014.

[54] Amir R. Zamir, Alexander Sax, William B. Shen, Leonidas J. Guibas, Jitendra Malik, and Silvio Savarese. Taskonomy: Disentangling task transfer learning. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, 2018.

[55] Howard Zhou, Tucker Hermans, Asmita Karandikar, and James Rehg. Movie genre classification via scene categorization. In *Proceedings of the 18th ACM International Conference on Multimedia*, pages 747–750, 10 2010. doi: 10.1145/1873951.1874068.