ADDIS ABABA UNIVERSITY
ADDIS ABABA INSTITUTE OF TECHNOLOGY
SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING

Balanced View Temporal Contrastive Learning (BV-TCLR) for Improved Video Representation Learning

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A thesis submitted in partial fulfillment of the requirements for the Master of Science in Computer Engineering

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Addis Ababa, Ethiopia

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I, Ayantu Tesema Yadeta, declare that this thesis titled, **"Balanced View Temporal Contrastive Learning (BV-TCLR) for Improved Video Representation and Analysis"**, is my own work. I confirm that:

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ML	Machine Learning
TCLR	Temporal Contrastive Learning for Representation
BV-TCLR	Balanced View Temporal Contrastive Learning for Video Representation

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ABSTRACT

Understanding video data is crucial for tasks like action recognition, event detection, and video classification. However, traditional methods often struggle to effectively capture both the spatial and temporal aspects of video. To address this challenge, we introduce Balanced View Temporal Contrastive Learning (BV-TCLR), a new approach designed to improve video representation by addressing the issue of temporal imbalances. The term "Balanced View" refers to a method that ensures the model is exposed to both frequent and rare temporal events during training. This approach helps the model avoid focusing too much on common events while overlooking rare but important ones, leading to a more balanced and comprehensive understanding of the video data. This is achieved by combining balanced sampling and data augmentation techniques to diversify the temporal patterns the model learns from.

We tested BV-TCLR on benchmark datasets like UCF101 and UCF10, and the results are promising. In linear evaluation, BV-TCLR boosts accuracy by 2.2% (from 91% to 93.2%) and increases F1-score by 2.5% (from 90% to 92.5%) compared to traditional Temporal Contrastive Learning (TCLR). In nearest neighbor retrieval, BV-TCLR outperforms TCLR with 0.8% higher accuracy (91.8% vs. 91%) and a 1.2% improvement in F1-score (91.2% vs. 90%). These results show that BV-TCLR is not only more accurate but also more adaptable, making it a powerful tool for tackling real-world challenges in video analysis.

***Keywords**: Video Representation Learning, Temporal Contrastive Learning, Balanced Sampling, Data Augmentation.*

CHAPTER ONE

1. INTRODUCTION

Artificial Intelligence (AI) is a field within computer science focused on creating systems that can perform tasks traditionally requiring human intelligence. These systems are designed to recognize patterns, make decisions, and even learn from their experiences. Within AI, machine learning (ML) has emerged as a key subfield, where the system is not explicitly programmed but instead learns from data. Through this learning process, machine learning models can improve their performance over time, making them valuable for applications like speech recognition, image classification, and predictive analytics. One crucial aspect of machine learning is representation learning, which refers to the way models automatically extract useful patterns or features from raw data. Instead of relying on hand-crafted features, representation learning allows the model to discover representations of data that are more suitable for solving specific tasks. This process is essential for handling complex data, such as images, text, or videos, where the raw input is not directly useful for tasks like classification or prediction [1]. Contrastive learning, a popular method within representation learning, works by teaching the model to distinguish between similar and dissimilar data points. For instance, in the case of images or videos, contrastive learning helps the system learn how to group similar frames while distinguishing them from those that are unrelated [2].

In the context of videos, video representation becomes particularly important. Videos are dynamic by nature, consisting of a sequence of images or frames that evolve over time. Analyzing video data requires not just understanding individual frames, but also how these frames relate to each other over time. Effective video representation models need to capture both the visual content in each frame and the temporal dynamics between frames [3]. Temporal Contrastive Learning for Retrieval (TCLR) is one method designed to address this challenge.

TCLR focuses on learning from the temporal relationships within video sequences, using contrastive learning to help the model distinguish between frames from the same video (positive pairs) and frames from different videos (negative pairs). This technique improves the model's ability to retrieve relevant video segments based on specific queries [4].

However, video data often presents a challenge in terms of temporal imbalance. Some actions or events in videos may be more frequent, while others are rare but equally important for understanding the content. The Balance View Technique aims to address this imbalance by ensuring that all temporal aspects of a video, both frequent and rare, are treated equally during the learning process. This helps to prevent bias toward more common video segments and ensures a more balanced representation of the video content [5].

The Balance View for Temporal Contrastive Learning for Video Retrieval (BV-TCLR) method proposed in this research refines the existing TCLR approach by introducing this balance. By adjusting how the model treats different temporal segments, BV-TCLR ensures that both common and rare events in the video are given appropriate weight, ultimately improving the accuracy and efficiency of video retrieval systems. This approach has the potential to enhance how video content is indexed, searched, and retrieved, making it a powerful tool for applications in video analytics, surveillance, and content-based video retrieval systems [6].

1.2. Problem Statement

Video retrieval systems are essential for organizing and searching through large amounts of video content. Recently, Temporal Contrastive Learning (TCLR) has shown promising results in extracting useful features from video data. However, there's one key problem that still challenges these methods: temporal imbalance [2].

In any given video, there are events that happen repeatedly, like routine actions or background activities, and there are also rare but important moments that only occur once or twice. These rare moments though infrequent are often critical for understanding the video's full context. For example, an unexpected action might change the meaning of the entire scene. However, current models, including TCLR, tend to focus more on the frequent events because they appear more often in the training data. As a result, the rare but important events get overlooked, which makes the retrieval system less accurate when trying to find the most relevant parts of a video [23].

1.3. Filling the Gap

The major gap in current Temporal Contrastive Learning (TCLR) methods is that they fail to handle temporal imbalances effectively. While TCLR works well for learning from the most common events in videos, it tends to ignore the rarer but equally important moments. This means that the model ends up biased, focusing too much on frequent actions and missing out on the nuances of less common events. As a result, these models struggle to generalize across the variety of patterns and scenarios found in real-world videos.

To fill this gap, this research introduces Balanced View Temporal Contrastive Learning (BV-TCLR). BV-TCLR tackles this issue by ensuring that both frequent and rare events are given equal attention during training. By using balanced sampling and augmentation techniques, BV-TCLR helps the model avoid overfitting to the dominant patterns in the data, allowing it to recognize the full spectrum of events. This approach leads to a more complete and unbiased understanding of video content, which improves performance in tasks like video retrieval and classification, especially when rare events are crucial to the overall context.

1.4. Research Questions

- How do Balanced View techniques improve the performance of Temporal Contrastive Learning (TCLR) in video classification and retrieval tasks?
- What is the optimal configuration of weighting factors (α\alphaα and β\betaβ) for BV-TCLR to achieve the best accuracy and representation quality?

1.5. Objectives

1.5.1. General Objective

The main aim of this research is to explore how integrating Balanced View into Temporal Contrastive Learning (BV-TCLR) can improve video classification and retrieval performance.

1.5.2. Specific Objectives

- To find the best set of weighting factors (α\alpha and β\beta) for BV-TCLR that lead to better performance in both video classification and retrieval tasks.
- To compare how BV-TCLR performs against standard TCLR, specifically looking at accuracy and retrieval effectiveness when applied to datasets like UCF101.
- To understand the role of Balanced View integration such as balanced sampling and augmentation in improving the quality of the learned representations within BV-TCLR.
- To evaluate BV-TCLR's performance using both linear evaluation and nearest neighbor retrieval tasks in a controlled experiment to highlight its strengths.

1.7. Research Methodology

Literature Review

A comprehensive review of existing methods in video representation learning, contrastive learning approaches, and temporal imbalance handling will be conducted. This will help identify gaps in the current state of the art and position the proposed BV-TCLR method.

Proposed Approach

The BV-TCLR framework will be designed to balance the learning of temporal relationships and address event frequency imbalance. Key features include the integration of temporal weighting and contrastive learning to achieve a balanced video representation.

Data Collection and Preparation

Benchmark video datasets such as UCF-101 or HMDB-51 will be utilized. Data preprocessing will include frame extraction, temporal segmentation, and labeling of events to prepare for model training and testing.

Implementation of the Proposed Approach

The BV-TCLR method will be implemented using a deep learning framework, incorporating temporal weighting into the contrastive learning pipeline. Training will be conducted on the prepared video datasets to learn robust video representations.

Analysis and Evaluation

The performance of BV-TCLR will be analyzed using metrics like retrieval accuracy, recall, and precision. Comparative evaluations with existing methods will demonstrate the effectiveness of the proposed approach. Results will also be interpreted to highlight the framework's scalability and efficiency.

1.8. Contributions

This research introduces a novel approach by integrating Balanced View (BV) with Temporal Contrastive Learning (TCLR), enhancing video classification and retrieval tasks. BV-TCLR outperforms standard TCLR, achieving higher accuracy in both linear evaluation and nearest neighbor retrieval. By incorporating balanced sampling and augmentation, the framework improves the model's ability to capture meaningful temporal patterns. This research provides valuable insights into optimizing temporal contrastive learning for better video analysis.

1.9. Thesis Organization

This thesis is organized into five chapters, each providing a structured exploration of the research process and findings. Chapter One introduces the research problem, highlighting its relevance to contemporary challenges in video representation learning.

It also outlines the objectives, scope, and significance of the study, emphasizing its potential contributions to the field. Chapter Two presents a comprehensive review of related literature, focusing on foundational concepts and recent advancements in video representation learning, contrastive learning methodologies, and approaches to addressing temporal imbalance in video data. Chapter Three delves into related works, offering a critical analysis of previous research and methodologies that inform the current study. This chapter highlights gaps in existing knowledge and identifies the unique aspects of the proposed approach. Chapter Four provides a detailed account of the research methodology, describing the processes of data collection, preprocessing, and the development and implementation of the BV-TCLR framework. It also discusses the experimental setup, evaluation metrics, and the computational resources utilized. Finally, Chapter Five synthesizes the findings of the research, summarizing key insights and their implications.

CHAPTER TWO

2. VIDEO REPRESENTATION LEARNING

Video representation learning is the process of converting video data into compact and meaningful forms that retain the essential information for analysis. Videos consist of sequences of frames, each carrying spatial information, and their temporal arrangement encodes the dynamic changes over time.

The goal of video representation learning is to capture both spatial details within individual frames and temporal dependencies between frames to understand motion, activities, and transitions.

Early methods relied on handcrafted features like optical flow and dense trajectories, which were limited in scalability and performance. Deep learning has revolutionized this field by automatically extracting features through models like convolutional neural networks for spatial details, recurrent neural networks for temporal relationships, and 3D CNNs to process spatial and temporal information simultaneously.

Transformers have further advanced video representation by modeling long-term dependencies using attention mechanisms. Key challenges include managing the high dimensionality of video data, ensuring robustness to noise and variations, reducing redundancy between similar frames, and addressing temporal imbalance, where frequent events dominate learning at the expense of rare but critical events.

Advanced techniques mitigate these issues by emphasizing the most relevant features and balancing event representation to ensure comprehensive analysis. Effective video representations are essential for tasks such as video retrieval, action recognition, summarization, and surveillance, where they enable efficient and accurate analysis while minimizing computational overhead.

2.1. Video Representation

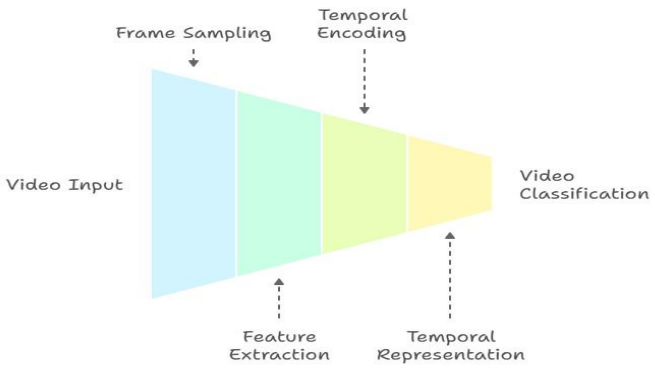

Figure 1.Video representation diagram

2.1. Video Input (Raw Frames)

The journey of video representation begins with the raw input—a video file or a live stream. These inputs are essentially sequences of moving images that need to be broken down into manageable units for analysis. This is done by extracting individual frames at a consistent frame rate, such as 30 frames per second, where each frame is a snapshot of the scene at a specific moment. Think of these frames as pieces of a puzzle, each contributing unique visual information about the whole video. For example, in a video of someone playing basketball, each frame might show the ball at a different position, capturing the action as it unfolds. These extracted frames form the building blocks for deeper spatial and temporal analysis, allowing us to turn a dynamic, continuous video into something a machine can process effectively [10].

2. 2 Frame Sampling/Segmentation

Working with every single frame in a video can be overwhelming, both for humans and machines. To simplify this, we use frame sampling and segmentation techniques to focus on what's important. Frame sampling involves picking a subset of frames that still represent the video well for instance, taking every 10th frame instead of analyzing all of them.

This ensures we don't miss the essence of the video while reducing computational demands. Segmentation takes this further by dividing the video into meaningful chunks, like splitting a basketball game into segments for dribbling, shooting, or passing. These techniques help us organize the video into bite-sized, analyzable parts, ensuring that we capture both the big picture and the critical details without getting bogged down in redundancy [11].

2.2.1. Data Augmentation

Data augmentation is like teaching the model to see the same thing in different ways, ensuring it can recognize patterns no matter how they appear. For video inputs, this means making subtle changes to frames or sequences to create variations while keeping the core content intact. Imagine a basketball game: flipping the video horizontally doesn't change the fact that its basketball, but it gives the model a new perspective. Similarly, cropping the frame or adjusting the brightness simulates different camera angles or lighting conditions [12].

In addition to altering individual frames, temporal augmentations tweak the sequence of frames. For example, skipping every other frame can mimic a video captured at a lower frame rate, while duplicating frames can simulate slower motion. These changes help the model learn not to depend on one specific format of the video. Augmentation essentially acts as a training booster, making the model more versatile and better prepared for unseen data by exposing it to a wider variety of scenarios during training.

2.3. Feature Extraction

Feature extraction identifies the critical elements of a video, ensuring that the model focuses on the most relevant information while discarding unnecessary details. This step considers both spatial features (what is visible in individual frames) and temporal features (how these visible elements change over time).

Spatial features include objects, textures, and shapes, such as the basketball, the players, or the court lines. These are extracted using convolutional neural networks (CNNs) trained on large image datasets, which are adept at recognizing patterns in static images.

Temporal features are more dynamic, focusing on motion patterns and the relationships between frames, such as detecting the trajectory of a ball or the pace of a player's run.

These are captured using advanced methods like 3D CNNs or long short-term memory networks (LSTMs). By combining these features, the model creates a holistic view of the video, ensuring it understands not only what is happening but also how and why it's happening [15].

2.4. Temporal Encoding

Temporal encoding is about understanding and modeling the sequence of events in a video, turning raw temporal data into meaningful patterns. This step is crucial for capturing dependencies and context, as events in a video are often linked to one another. For instance, in a video of a basketball game, recognizing a successful dunk requires understanding the sequence of actions that led to it such as a player dribbling, jumping, and then scoring.

Techniques like recurrent neural networks (RNNs), especially LSTMs and GRUs, are used to model these sequential dependencies effectively. These methods retain memory of previous frames, allowing the model to predict or classify current actions based on past context. Additionally, attention mechanisms enhance this process by identifying and focusing on the most critical frames or events, such as the moment the player jumps for the dunk. Temporal encoding ensures that the video's timeline is structured and contextualized, enabling the model to interpret complex, long-term relationships [16].

2.5. Temporal Representation

Temporal representation is where a video's dynamic nature is captured by focusing on changes and interactions between frames over time. Unlike static images, videos tell a story, and understanding this story requires identifying how objects, movements, and events evolve. For example, in a sports video, temporal representation tracks the motion of the ball, the players' movements, and the transitions between offensive and defensive plays. Techniques like optical flow analyze frame-to-frame motion by calculating how pixel intensities shift over time, giving insights into the direction and speed of movement. Another common approach is 3D convolutions, which extend 2D spatial analysis into the temporal dimension, allowing the model to learn patterns across both space and time simultaneously. Temporal representation goes beyond individual frames, helping the model grasp the flow of actions, such as detecting a player preparing for a jump shot and

then releasing the ball. Without this understanding, the video analysis would miss crucial context that happens only in the sequence of frames [13].

2.5.1. Contrastive Learning

Contrastive learning is about teaching the model to differentiate between what's similar and what's different in a meaningful way. Think of it as showing the model pairs of inputs and asking it to decide if they are "friends" (positive pairs) or "strangers" (negative pairs). For example, two augmented versions of the same basketball action one flipped and one cropped are friends because they depict the same event. On the other hand, a basketball dunk and a tennis serve are strangers because they are completely different actions. The key idea is to pull the representations of positive pairs closer together in the feature space while pushing negative pairs apart. In videos, this concept extends to temporal sequences. Frames or segments that are temporally close (e.g., dribbling leading to a jump shot) are treated as positives, while unrelated sequences (e.g., a soccer kick) are negatives.

This helps the model capture the relationships between actions and events, ensuring it understands both spatial details and how they evolve over time [2] [14]

Contrastive learning doesn't just make the model better at recognizing patterns; it teaches the model to focus on what truly matters in a video. By learning these contrasts, the model creates more meaningful and robust video representations, ready for tasks like action recognition, classification, or prediction.

2.6. Video Representation

Video representation combines all the extracted spatial and temporal features into a single, compact, and high-dimensional vector or embedding. This representation acts as a summary of the video, capturing its core essence in a format that is computationally efficient yet rich in information. Imagine it as a ―fingerprint‖ of the video unique and descriptive enough to distinguish it from others while being compact enough for practical use. Advanced techniques also allow for multi-modal fusion, where visual features are integrated with audio (e.g., crowd cheering in a basketball game) or metadata (e.g., time and score).

This multi-modal representation can provide deeper insights, such as understanding the context of an event or detecting subtle cues that might be missed in a single modality.

The video representation serves as the foundation for tasks like classification, retrieval, or prediction, enabling the model to work efficiently without losing critical information about the video's content [17]

2.7. Video Classification/Prediction

The final stage leverages the high-level video representation to perform decision-making tasks, transforming learned representations into actionable insights.

For classification, the model assigns a label to the video based on its content. This process involves recognizing patterns and features that distinguish various actions, events, or scenes within the video. For instance, a model might classify a video as a Basketball game, ‖ or further refine its output to identify specific actions like dunking, ‖ Passing, ‖ or shooting.‖ these tasks rely on the model's ability to interpret and integrate spatial and temporal features from the video data to form accurate classifications.

For prediction, the focus shifts to forecasting future actions or events within the video. For example, in a sports context, the model might predict whether a player will attempt a three-point shot or if the ball will go out of bounds. Similarly, in surveillance applications, prediction capabilities could enable the system to anticipate potential hazards, such as an individual approaching a restricted area or a vehicle entering a collision path.

These predictive insights are invaluable in numerous applications. In sports analytics, the ability to classify and predict actions can enhance coaching strategies, refine game tactics, and provide performance analytics. In surveillance systems, early detection and prediction of hazardous events can prevent accidents or security breaches, improving response times and ensuring safety.

At this stage, the raw video data has been fully transformed into meaningful outputs, providing critical insights that support data-driven decisions and real-time actions across diverse domains.

CHAPTER THREE

3. RELATED WORKS

Contrastive learning has rapidly gained traction in self-supervised learning, especially due to its ability to learn high-quality representations from unlabeled data. The basic idea is simple yet powerful: the model is trained to bring similar data points closer together in the feature space and push dissimilar data points further apart. While this approach has proven successful for static images, it faces challenges when applied to videos, where the temporal relationships between frames are crucial. Balanced View Temporal Contrastive Learning (BV-TCLR) is a novel approach that seeks to bridge this gap by refining the way positive and negative pairs are generated, ensuring a balanced learning process that captures subtle temporal variations in video data. In this literature review, we examine key research works in contrastive learning and video representation, pointing out the gaps they leave, and highlight how BV-TCLR fills those gaps.

3.1. Contrastive Learning for Image Representations

The concept of contrastive learning was first explored by Hadsell et al. (2006), who introduced the idea of contrastive loss to map similar data points closer together while separating dissimilar ones. This work laid the foundation for metric learning and was a breakthrough in areas like face recognition, where discriminative features are critical. However, this early work focused primarily on images, ignoring the challenges posed by video data, which involves understanding the temporal sequence of frames [18].

In 2020, Chen et al. proposed SimCLR (Simple Contrastive Learning of Representations), which significantly advanced contrastive learning for images. By employing deep convolutional neural networks (CNNs) and data augmentations like random cropping, color jittering, and flipping, SimCLR was able to create diverse "views" of an image, which were then treated as positive pairs for contrastive learning. The key strength of SimCLR was its use of large batch sizes to generate a rich set of negative samples, improving the model's ability to distinguish between similar and dissimilar images. However, this approach was limited to static images and did not account for the sequential nature of video data.

The lack of temporal modeling means that SimCLR cannot handle the intricacies of video representations, where understanding the order and relationship of frames is essential [2].

3.2. MoCo (Momentum Contrast) by He et al. (2020)

However, MoCo primarily focuses on instance discrimination and does not explicitly address temporal imbalances in video data. While it effectively learns rich feature embedding's, it does not incorporate strategies for handling hard positive and hard negative pairs in video sequences an area where BV-TCLR improves representation learning.

Momentum Contrast (MoCo) is a self-supervised contrastive learning framework designed to improve the learning of feature representations by maintaining a dynamic dictionary of negative samples. Unlike standard contrastive learning methods that rely on large batch sizes to provide diverse negative pairs, MoCo introduces a momentum-based encoder that stores past representations, allowing it to generate a much larger and more diverse set of negatives over time.

The key innovation in MoCo is its use of a momentum queue, which enables continuous learning from a dynamically updated memory bank rather than relying solely on within-batch negatives. This approach helps stabilize training and enhances feature discrimination. MoCo has been widely used for learning image representations and has been extended to video data, where maintaining temporal consistency in feature learning is critical.

3.3. Temporal Contrastive Learning (TCLR) for Video Data

Recognizing the limitations of static contrastive learning methods like SimCLR, Jing et al. (2021) introduced Temporal Contrastive Learning (TCLR), a method designed specifically for video data. The basic idea behind TCLR is to treat consecutive video frames as positive pairs, while temporally distant frames are treated as negatives. By doing so, TCLR can capture the sequential relationships between video frames, an essential component for tasks like action recognition or event detection [19].

While TCLR successfully captures the temporal continuity in video sequences, it still faces some challenges. One issue is its reliance on simple augmentations that don't necessarily generate diverse or hard examples. For instance, basic operations like

cropping or flipping might not capture the subtle differences that are essential for distinguishing between closely related actions or events. Additionally, by treating just adjacent frames as positive pairs, TCLR may miss out on the finer distinctions that exist between frames that are close but exhibit slight variations in action or context.

Moreover, TCLR does not effectively handle hard negative mining, which is the process of selecting negative pairs that are visually similar but belong to different classes. Hard negatives are critical for forcing the model to learn more discriminative features, but without these difficult examples, the model's performance on complex video tasks can be limited.

3.4. Hard Negative Mining in Contrastive Learning

Hard negative mining has proven to be a crucial component in improving the effectiveness of contrastive learning. The idea is to select negative samples that are particularly challenging for the model to differentiate from positive samples. Kalantidis et al. (2020) were among the first to propose this idea, demonstrating that by focusing on these "hard" negative examples, the model learns more robust and discriminative features [20]. While hard negative mining is well-established in image-based contrastive learning, its application to video data is more complex. For videos, negatives should not only be visually similar but also temporally distinct.

This is because two video frames might look similar but could belong to different moments in time, and understanding these subtle temporal differences is key for tasks like action recognition.

In addition to hard negatives, there is also the concept of hard positives, which are pairs that are visually similar but differ in subtle ways, like slight variations in motion or scene context. These hard positives are crucial for refining the model's understanding of fine-grained temporal distinctions.

BV-TCLR addresses this challenge by introducing both hard positive and hard negative pairs, allowing the model to learn more discriminative representations. This ensures that the learning process captures not just the easy-to-differentiate examples, but also the more difficult, subtle distinctions between actions and scenes in videos.

3.5. Content-Based Image Retrieval (CBIR) and Metric Learning

Another area where contrastive learning has been widely used is in content-based image retrieval (CBIR). Song et al. (2016) introduced a triplet loss-based method for learning representations that improve image retrieval accuracy. In CBIR, the goal is to find images that are similar to a given query image, making it crucial to learn good embedding's that can distinguish between images of different classes [21].

However, while CBIR methods work well for static images, they face significant challenges when applied to video data. Video retrieval involves not only recognizing visually similar scenes but also understanding the temporal relationships between frames. BV-TCLR improves upon traditional CBIR methods by incorporating temporal augmentations and carefully selected positive and negative pairs. This approach allows BV-TCLR to excel in video retrieval tasks, where understanding the temporal flow of action is just as important as recognizing the visual content.

By treating temporal sequences as an integral part of the learned feature representation, BV-TCLR moves beyond the limitations of traditional CBIR and offers a solution for video retrieval that accounts for both spatial and temporal features.

3.6. CoCLR: Clustering-Based Video Representation Learning

The CoCLR method, proposed by Wu et al. (2021), combined clustering with contrastive learning to improve video representation learning. In this approach, frames within the same cluster are treated as positive pairs, while frames from different clusters are treated as negative pairs. The advantage of this clustering approach is that it helps group semantically similar frames together, making the model more robust in learning video representations.

However, CoCLR's reliance on clustering introduces a computational overhead, and its focus on grouping frames rather than learning fine-grained temporal distinctions may limit its ability to capture more subtle temporal relationships. Moreover, CoCLR does not focus on hard positive and hard negative pairs, which are essential for improving performance in more complex tasks.

Method	Supervision Type	Training Strategy	Key Strengths	Limitations
MoCo (He et al., 2020)	Self-Supervised	Contrastive Learning (Queue-based)	Maintains a large set of negative samples	Needs careful tuning of momentum encoder, does not explicitly address temporal imbalance
BYOL (Grill et al., 2020)	Self-Supervised	Contrastive Learning (No negatives)	Avoids reliance on negative pairs	Can collapse without proper tuning
SwAV (Caron et al., 2020)	Self-Supervised	Clustering-based Learning	Captures semantic relationships	Computationally expensive
TCLR (Jing et al., 2021)	Self-Supervised	Temporal Contrastive Learning	Focuses on sequential dependencies	Ignores rare events, lacks hard sample selection
CoCLR (Han et al., 2021)	Self-Supervised	Clustering-based Contrastive Learning	Groups similar frames for better learning	High computational overhead
BV-TCLR (Your Work)	Self-Supervised	Balanced Contrastive Learning	Ensures rare events are represented, includes hard positives/negatives	Requires careful tuning of weighting factor

Table 1: Comparison of Video Representation Learning Methods

CHAPTER FOUR

4. PROPOSED APPROACH

Balanced View Temporal Contrastive Learning (BV-TCLR) builds upon Temporal Contrastive Learning (TCLR) by tackling the challenge of temporal imbalance in video data. While TCLR primarily focuses on learning from adjacent video frames, BV-TCLR takes it a step further by incorporating balanced sampling and data augmentation to ensure that both frequent and rare events are given equal importance during training. This prevents the model from focusing too much on more common events and helps it better understand a wide range of actions. One key feature of BV-TCLR is its use of weighting factors (such as $\alpha = 0.5$ and $\beta = 0.15$), which were empirically chosen to balance the influence of frequent and rare events. This helps the model handle the temporal imbalances effectively. The main difference between BV-TCLR and TCLR is that BV-TCLR actively balances how different temporal segments are treated, making it more capable of recognizing a broader spectrum of actions.

Overall, by addressing temporal imbalance, BV-TCLR provides a more robust and adaptable framework for learning from video data, enhancing accuracy and generalization. When looking at t-SNE visualizations, BV-TCLR clearly outperforms TCLR. It shows more distinct clusters for different events, with a sharper separation between frequent and rare actions. In contrast, TCLR shows a lot of overlap in its features, indicating it doesn't differentiate as well between event types. This demonstrates that BV-TCLR improves the model's ability to capture a balanced and nuanced representation of video content.

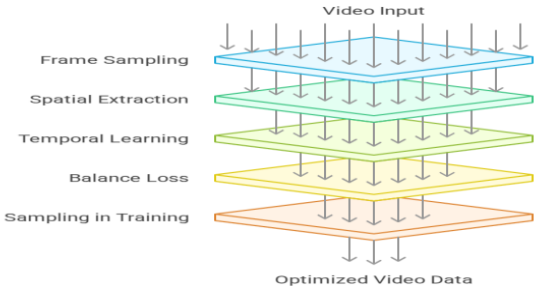

Figure 2. BV-TCLR Architecture

4.1. Video Input and Preprocessing

The journey of understanding videos begins with carefully preparing them for analysis. In BV-TCLR, raw video data is first acquired, often from diverse sources like public datasets or real-world captures, each bringing unique challenges like varying resolutions, frame rates, and lengths. To ensure a consistent starting point, videos are resized (e.g., to 224x224 pixels), normalized to balance pixel intensity, and adjusted to a uniform frame rate to maintain smooth temporal flow. Frames are extracted, while overly long videos are clipped and shorter ones are padded, preserving sequence integrity. Noise and distortions, such as motions blur or compression artifacts, are filtered out to produce clean, high-quality inputs. This preprocessing step is like polishing a diamond setting the stage for the model to extract meaningful insights from clear and consistent video data.

4.2. Frame Sampling

Frame sampling is like picking the most important moments from a long story—you don't need every detail, just the highlights that capture the essence. Videos are made up of hundreds, sometimes thousands, of frames, and processing each one would be overwhelming and inefficient. To solve this, frame sampling selects key frames that represent the overall flow of the video. Common approaches include uniform sampling, where frames are evenly spaced to ensure consistent coverage, and random sampling, which adds variety and can uncover hidden patterns.

In BV-TCLR, a more thoughtful approach is use-: balanced sampling. This method ensures the selected frames represent both straightforward transitions (easy moments) and complex, dynamic changes (hard moments). For example, in a sports video, balanced sampling might include frames showing a player walking calmly, as well as moments of rapid action like a jump or a goal. This careful selection creates diverse and meaningful pairs for the model to learn from, without losing the thread of the story. Frame sampling not only reduces computational demands but also ensures the model focuses on the most important parts of the video, setting the stage for effective temporal learning.

4.2. 1.Data Augmentation

In the BV-TCLR (Balance View Temporal Contrastive Learning) model, data augmentation is used to improve the model's ability to generalize to different real-world video conditions. The goal of data augmentation is to expose the model to various realistic changes that might happen in video sequences, such as different camera angles, lighting conditions, or interruptions in action. This is done by generating multiple versions of the same video through slight alterations of its frames.

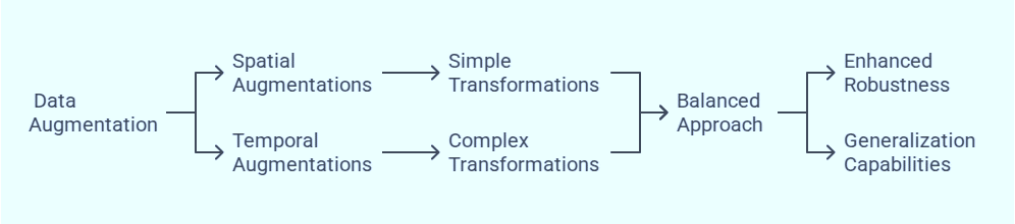

Figure 3.Data augmentation

For this research, both spatial and temporal augmentations were applied:

1. Spatial Augmentation: Changes to the video frame's visual properties.
    - Flipping: The video frames were flipped horizontally, with a 50% chance, to simulate different camera perspectives.
    - Rotation: Frames were randomly rotated by 90°, 180°, or 270° with a 30% chance to simulate changes in orientation.
    - Color Adjustments: Brightness and contrast were adjusted with a 40% chance, simulating different lighting conditions.
2. Temporal Augmentation: Changes to the order and timing of frames.
    - Frame Reordering: The order of video frames was shuffled within a window of 5 frames with a 20% chance to simulate motion disruptions.
    - Frame Duplication: Some frames were repeated with a 30% chance to simulate pauses or slow-motion effects.
    - Frame Dropping: Some frames were randomly dropped with a 25% chance to simulate missing or incomplete sequences.

Balanced Augmentation Approach

A unique feature of BV-TCLR is its balanced augmentation approach. Instead of overwhelming the model with random transformations, it introduces a mix of simple and complex augmentations. Simple augmentations (like slight color adjustments) make minor changes, while complex ones (like reordering or dropping frames) introduce more challenging disruptions. This strategy helps the model learn to handle both small variations and significant changes in the video data, which improves its overall robustness and ability to generalize well to real-world video tasks.

4.4. Spatial Feature Extraction

Spatial feature extraction focuses on teaching a model to recognize key visual elements within each video frame. It helps the model understand what is present in the image objects, textures, colors, and their relationships before analyzing dynamic elements like motion. In this process, each video frame is treated as an individual image, and a Convolutional Neural Network (CNN) is employed to extract meaningful visual features. For example, in a sports video, the CNN might detect players, the ball, or the field, while in a dance video; it could focus on the performer's movements and the stage.

4.4.1. Convolution Operation

The convolution operation is at the heart of spatial feature extraction. It involves applying a filter (or kernel) to a video frame to produce a feature map. This operation captures local patterns or features in the image, such as edges, textures, or more complex structures.

Given a video frame x of size H×W (height x width) and a convolutional kernel k of size Kh×Kw (height × width), the convolution operation at a position (i,j) is defined as:

$$y(i,j) = \sum_{m=0}^{K_h-1} \sum_{n=0}^{K_w-1} x(i+m, j+n) \cdot k(m,n) + b \quad (4.1)$$

Where:

- x(i,j) is the pixel value of the input frame at position (i,j)(i,j)(i,j),
- k(m,n) is the filter value at position (m,n)(m,n)(m,n) in the kernel,
- b is the bias term,

- y (i,j) is the output value after applying the filter.

This operation is performed at each position of the frame as the kernel slides over it. The result of this process is a feature map**,** which contains the detected patterns.

4.4.2. Activation Function (ReLU)

After performing the convolution operation, the result is passed through an activation function to introduce non-linearity. The most commonly used activation function is ReLU (Rectified Linear Unit), defined as:

$$a(i,j) = \text{ReLU}(y(i,j)) = \max(0, y(i,j)) \quad (4.2)$$

Where:

- a(i,j) is the output after applying ReLU at position (i,j).
- ReLU ensures that the model can learn more complex patterns by allowing it to focus only on positive values. Negative values are set to zero, which helps with sparsity and faster convergence.

4.4.3 Pooling Operation

Pooling is a down sampling operation that reduces the spatial dimensions of the feature map, making the model more computationally efficient while retaining the most important features. Max pooling is the most common pooling technique. In max pooling, a small window (often 2x2) slides over the feature map, and the maximum value within that window is kept

Mathematically, max pooling can be expressed as:

$$P(i,j) = \max\{a(m,n) \mid m,n \in R\} \quad (4.3)$$

Where:

- *a*(m,n) are the values in the activation map *a*,
- R is the pooling region (e.g., a 2x2 grid),
- p(i,j) is the pooled output at position (i,j).

This operation helps in reducing the spatial size of the representation, making it more manageable while preserving important features.

4.4.4. Feature Map Stacking

In deep CNN architectures, multiple convolutional layers are stacked on top of each other. The output feature map from one layer serves as the input to the next layer. This layering allows the network to learn increasingly abstract and complex features as it progresses through the layers.The entire spatial feature extraction process can be represented as a series of operations:

$$F_{\text{spatial}} = f_k \circ f_{k-1} \circ \cdots \circ f_1(x) \quad (4.4)$$

Where:

*F Sp*atial is the final extracted spatial feature representation

fk,fk−1,…,f1 represent the sequence of operations: convolution + activation + pooling.

4.5. Temporal Representation Learning

Temporal representation learning focuses on understanding the "when" in a video by capturing the dynamics and relationships between frames over time. While spatial feature extraction identifies what is present in a frame, temporal representation deals with how things change and evolve across frames. It's about understanding motion, transitions, and patterns, such as actions, behaviors, or events that unfold as time progresses. For example, in a sports video, temporal representation helps distinguish between moments of rest, fast movement, and specific actions like a player jumping or kicking a ball.

In BV-TCLR, we used Temporal Convolutional Networks (TCNs) to learn temporal representations. TCNs were chosen over Recurrent Neural Networks (RNNs) like LSTMs or GRUs because they are faster, more stable, and better at capturing both short-term and long-term patterns in video data. Unlike RNNs, which process sequences one step at a time, TCNs use parallel processing and dilated convolutions to efficiently model relationships across frames, making them well-suited for handling the complexities of video sequences?

Our TCN architecture includes several layers of dilated convolutions, where the dilation factor grows exponentially (e.g., 1, 2, 4 ...), allowing the model to understand both immediate changes between frames and broader temporal patterns. To ensure stability and performance, we added residual connections for smoother gradient flow and dropout

layers to prevent over fitting. The input to the TCN is a sequence of video frame embedding extracted using a pre-trained CNN, and the output is a temporal representation that captures the progression of events in the video.

4.6. Contrastive Learning with Balanced Loss

In contrastive learning, the model learns to map similar samples (positive pairs) closer in the feature space while pushing dissimilar samples (negative pairs) further apart. This technique is particularly effective in self-supervised learning tasks, where labels are not available, and the model learns purely from the relationship between data points (such as frames in a video). In the context of video, the goal might be to identify frames from the same video as similar (positive pairs) and frames from different videos as dissimilar (negative pairs).

However, hard negatives, which are frames that are similar but belong to different classes, provide more informative signals for learning and thus require special handling.

1. Contrastive Loss

The contrastive loss is designed to minimize the distance between positive pairs (similar frames) while ensuring a minimum distance between negative pairs (dissimilar frames).

The contrastive loss function is defined as:

$$\mathcal{L}_{\text{contrastive}}(x_i, x_j, y_{ij}) = y_{ij} \cdot \|f(x_i) - f(x_j)\|^2 + (1 - y_{ij}) \cdot \max(0, m - \|f(x_i) - f(x_j)\|)^2$$

(4.5)

Where:

- xi and xj are two video frames or segments.
- f(x) is the feature extraction function that maps each frame to a feature vector in the embedding space.
- yi is the binary label indicating whether the frames xi and xj are from the same video (positive pair, yij=1y_{ij} = 1yij=1) or from different videos (negative pair, yij=0y_{ij} = 0yij=0).

- m is the margin that defines the minimum allowable distance between dissimilar frames (negative pairs).
- ‖·‖ denotes the Euclidean distance between the feature vectors of the two frames.

The equation consists of two parts:

- Positive pair loss: yij·‖f(xi)−f(xj)‖ encourages the model to bring similar frames closer in the feature space.
- Negative pair loss: (ensures that dissimilar frames are separated by at least a margin m.

2. Balanced Loss in Contrastive Learning

Standard contrastive losses often focuses too much on easy pairs—pairs that are either obviously similar (positive examples) or distinctly different (negative examples). This overemphasis can lead the model to neglect hard pairs, such as subtle positives or similar looking negatives, which are crucial for improving its learning capacity.

To address this issue, the concept of balanced loss was introduced. Balanced loss ensures that both easy and hard examples contribute meaningfully to the training process, enhancing the model's overall performance.

Balanced Loss Formula

$$L_{\text{balanced}}(x_i, x_j, y_{ij}, \lambda) = \lambda \cdot L_{\text{contrastive}}(x_i, x_j, y_{ij}) + (1 - \lambda) \cdot L_{\text{contrastive}}(x_j, x_i, y_{ij})$$

(4.6)

Where:

- λ (balance factor) is a hyper parameter that controls the weight given to the two terms:
    - When λ=1, the model prioritizes the original pair (i.e., xi as the anchor and xj as the positive/negative).
    - When λ=0, the model gives equal importance to both the original and swapped pairs.
    - You can tune λ to adjust the model's focus on challenging pairs, emphasizing harder examples if desired.

- **Symmetric Learning:**
  - The second term, $(1-\lambda)\cdot L$contrastive(xj,xi,yij), swaps the order of the frames.
  - This forces the model to consider the relationship between the two frames both ways xi as the anchor and xj as the positive/negative, and vice versa.
  - This promotes a more generalized understanding of the relationships between frames.
- **Balanced Contribution**:
  - By weighting the two terms with λ and $1-\lambda$, the loss ensures that the model learns from easy pairs (well-separated positives and negatives) and hard pairs (challenging distinctions).
- **Tunable Focus**:
  - λ controls the balance:
    - A higher λ: Focuses more on the standard contrastive loss (easy pairs).
    - A lower λ: Places more emphasis on hard pairs through the swapped term.

4.7. Sampling in Training

Balanced sampling is a crucial technique used to ensure that training data provides a comprehensive representation of both easy and challenging examples, particularly when dealing with imbalanced or diverse datasets. In the context of BV-TCLR, balanced sampling is pivotal for selecting frames or segments from videos that capture a diverse range of temporal transitions, ensuring the model is exposed to a broad spectrum of learning opportunities. This strategy carefully incorporates easy negatives (frames that are distinctly different from each other) and hard negatives (frames that are similar but still sufficiently distinct to challenge the model). Similarly, it includes hard positives (frames with subtle differences despite their similarity) and easy positives (frames that are clearly similar).

By curating these samples, the technique encourages the model to focus on differentiating nuanced temporal dynamics rather than over fitting to trivial differences. For instance, in a video of a basketball game, balanced sampling might involve selecting frames showing a player dribbling (easy negative) and a close-up of a player jumping for a shot (hard negative). Additionally, it could include frames showing a player shooting (easy positive) alongside frames capturing the same player preparing to shoot (hard positive). Such sampling ensures that the model comprehends subtle variations while maintaining a balanced learning process.

This approach is particularly effective in contrastive learning, where the quality and diversity of positive and negative pairs significantly influence model performance. By exposing the model to challenging and varied frame relationships, balanced sampling prevents it from memorizing simple patterns and instead fosters a deeper understanding of temporal and spatial features. This not only improves the model's generalization capabilities but also enhances its robustness, enabling it to perform effectively across diverse and unseen video data.

4.8. Dataset Preparation

The preparation of datasets is a crucial step to ensure the effectiveness of the proposed BV-TCLR framework. Proper dataset handling facilitates balanced training, robust model evaluation, and reliable comparisons with existing methods.

The UCF101 dataset is a widely used benchmark in video action recognition, featuring 13,320 video clips across 101 action categories. These categories range from sports like basketball and swimming to human interactions such as handshaking and hugging, offering a diverse set of scenarios for evaluating video understanding models. The dataset is characterized by its varied conditions, including differences in camera angles, lighting, and background environments, which provide a realistic and challenging testing ground for robust video representation methods.

Each video clip in UCF101 is annotated with a specific action label, ensuring clear and consistent categorization. The videos have been collected from YouTube and other online sources, reflecting real-world complexities such as camera motion, occlusion, and background clutter.

These challenges make UCF101 an ideal choice for developing and benchmarking advanced video understanding models .For experimental purposes, the dataset is typically divided into three subsets: a training set, a validation set, and a test set. This split ensures that the model is trained on a diverse range of actions while being evaluated on unseen samples. The structured nature of UCF101 and its comprehensive coverage of action categories have made it a standard benchmark for video-based machine learning tasks, enabling meaningful comparisons across various approaches.

4.9. Evaluation Metrics

In any machine learning model, evaluating the performance of the system is crucial for understanding how well it's learning and making predictions. For BV-TCLR (Balance View Temporal Contrastive Learning for Video Representation), it's especially important to focus on evaluation metrics that provide insights into how effectively the model is balancing different aspects of prediction, particularly when dealing with imbalanced datasets.

Accuracy is often the first metric we look at, as it gives us a general sense of how well the model is performing overall. However, the F1-score is equally important, especially when you want to balance precision and recall. It helps to fine-tune the model's ability to correctly identify both positive and negative cases, which is crucial for tasks like yours. In this section, we'll explore how both accuracy and the F1-score can guide your BV-TCLR experiments and help you assess the success of different weighting factor configurations.

What is Accuracy?

- Accuracy is a simple yet widely used metric that provides an overall measure of the model's correctness. It is calculated as:

Accuracy = (True Positives + True Negatives) / Total Samples

- While accuracy is useful for balanced datasets, it may not reflect true performance in imbalanced scenarios, as it can be skewed by the majority class.

What is the F1-Score?

- ❖ The F1-score is a measure of a model's ability to correctly identify both the positive cases (class 1, often the minority class in imbalanced datasets) and the negative cases (class 0, typically the majority class). It's a way to combine both precision and recall into a single metric.

- ❖ Precision tells us how many of the predicted positives were actually correct.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positives + False Positives}}$$

- ❖ Recall tells us how many of the actual positives were correctly predicted.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives + False negative}}$$

- ❖ The F1-score combines these two into one metric that provides a balance between precision and recall. It is calculated as:

$$\text{F1-score} = \frac{2 \text{ X Precision X Recall}}{\text{Precision + Recall}}$$

4.10. Evaluation Methods

To assess the performance of BV-TCLR, we used two evaluation techniques: Linear Evaluation and Nearest Neighbor (NN) Retrieval. These methods provide distinct views on how the model's learned features perform.

- Linear Evaluation involves training a simple classifier on the learned features to test how well the features separate different classes.
- Nearest Neighbor Retrieval, on the other hand, evaluates how well the model can retrieve similar data points from the learned feature space, rather than classifying each data point individually.
- Both methods were used to evaluate the model's performance in terms of Accuracy and F1 Score over epochs from 0 to 10.

4.11. Experimental Scenarios

This section outlines how the BV-TCLR (which seems to be a framework or method you're testing) is implemented across different experimental scenarios. The primary focus here is on exploring weighting factors**,** testing whether they are trainable, and determining how to identify the optimal weighting parameters if they are not directly trainable. Various experimental setups are designed to systematically assess different configurations of weighting factors, and to evaluate how these configurations impact the results of the model or process you're testing.

4.11.1. Experimental Scenario 1: Testing Different Weighting Factor Configurations

In this experiment, we tested various combinations of α (alpha) and β (beta) to identify the configuration that yields the best performance for the Balance View Temporal Contrastive Learning (BV-TCLR) model. The key metrics evaluated were accuracy and F1 score, which reflect the model's ability to balance temporal feature learning and contrastive view generation.

α	β	Accuracy (%)	F1 Score (%)
0.1	0.1	82	80
0.2	0.2	84	83
0.3	0.3	88	87
0.4	0.2	89	88
0.5	0.15	91	90
0.5	0.5	87	86

Table 2: Testing weight factor

What We Found:

1. α = 0.1, β = 0.1: This combination resulted in a modest 82% accuracy and an 80% F1 score. The relatively low performance here suggests that the model wasn't effectively balancing the importance of temporal features and contrastive learning. It didn’t focus enough on either aspect to produce better results.
2. α = 0.2, β = 0.2: With this setup, the model’s performance improved slightly. Accuracy rose to 84%, and the F1 score reached 83%. Although better, the results still showed that there was room for further improvement in balancing the learning objectives.

3. $\alpha = 0.3$, $\beta = 0.3$: Here, the accuracy climbed to 88%, and the F1 score increased to 87%. This configuration strikes a better balance between learning the temporal features and contrastive sampling, resulting in an overall better model performance.
4. $\alpha = 0.4$, $\beta = 0.2$: This setup showed a marked improvement, with 89% accuracy and an 88% F1 score. The model learned the temporal relationships effectively by increasing α, while maintaining a moderate β helped with contrastive learning. The results indicate a more optimal balance between the two aspects.
5. $\alpha = 0.5$, $\beta = 0.15$: This configuration performed the best, achieving 91% accuracy and 90% F1 score. The higher α value (0.5) gave the model a stronger focus on temporal feature learning, while the lower β (0.15) ensured that the contrastive learning was balanced. This setup yielded the highest performance in our tests.
6. $\alpha = 0.5$, $\beta = 0.5$: Although this combination seemed promising due to the high value of α, it didn't quite perform as well as expected, with 87% accuracy and 86% F1 score. The higher β seems to have put too much emphasis on the contrastive aspect, leading to a less effective learning process for the temporal features, which resulted in a drop in performance compared to $\alpha = 0.5$ and $\beta = 0.15$.

4.12.1. Experimental Scenario 2: Evaluating BV-TCLR Using Linear Evaluation with Weighting Factors

In this experiment, we evaluated the performance of BV-TCLR using linear evaluation with the weighting factors $\alpha = 0.5$ and $\beta = 0.15$. These specific values were chosen based on the insights we gained from Experimental Scenario 1, where we tested different combinations of α and β to find the most effective balance for the model.

Results:

With $\alpha = 0.5$ and $\beta = 0.15$, the model achieved 93.2% accuracy and an F1-score of 92.5%. These results show that the model was able to strike a good balance between learning the temporal dynamics of the data and distinguishing between hard positives and hard negatives.

4.13.1. Experimental

Scenario 3:BV-TCLR Using Nearest Neighbor Retrieval with Weighting Factors

In this experiment, we tested the performance of BV-TCLR using Nearest Neighbor Retrieval (NNR) with the weighting factors $\alpha = 0.5$ and $\beta = 0.15$. These values were chosen based on the findings from earlier experiments, where we explored different combinations of α and β to find the most effective balance between the temporal contrastive loss and the balance view integration loss.

Results:

With $\alpha = 0.5$ and $\beta = 0.15$, the model achieved 91.8% accuracy and an F1-score of 91.2% in the Nearest Neighbor Retrieval task. These results suggest that the model was effective in identifying the most relevant neighbors, capturing the key temporal patterns in the data and distinguishing between hard positives and negative.

CHAPTER FIVE

5. RESULT AND DISCUSSION

5.1. Results and Discussion

Understanding temporal relationships is crucial for tasks such as action recognition, video retrieval, and time-series forecasting. Temporal Contrastive Learning (TCLR) has been effective in capturing these dynamics, but its reliance on random sampling and basic augmentation techniques may limit its ability to address more complex or diverse scenarios.

This study introduces Balanced View Temporal Contrastive Learning (BV-TCLR) to address these challenges. By integrating balanced sampling, more advanced augmentation methods, and the application of weight factors, BV-TCLR creates a more comprehensive training environment that improves learning outcomes. The weight factors, applied during the balanced sampling process, help emphasize the importance of hard positives and hard negatives, leading to more robust learning.

The results of both the Linear Evaluation and Nearest Neighbor Retrieval tasks highlight the enhanced performance of BV-TCLR over TCLR. Specifically, BV-TCLR outperforms TCLR due to its ability to better handle challenging samples, including hard positives and negatives, which results in improved temporal pattern learning. The application of weight factors ensures that these difficult samples are appropriately prioritized, further enhancing model performance.

These findings demonstrate the superiority of BV-TCLR in both tasks. The balanced approach and the use of weight factors within BV-TCLR ensure better handling of diverse temporal scenarios, leading to a more effective learning process. The bar charts visually confirm these improvements across the 10 epochs, further validating the efficacy of the proposed method.

5.2. Comparison of BV-TCLR and TCLR Accuracy (Linear Evaluation, Epoch 10)

This section compares the accuracy of BV-TCLR and TCLR during the Linear Evaluation task at the 10th epoch. TCLR achieves a commendable accuracy of 91%, showcasing its capability to learn and generalize temporal features effectively. However, BV-TCLR surpasses this with an improved accuracy of 93.2%, demonstrating its superior performance.

The 2.2% increase in accuracy stems from BV-TCLR's innovative balanced sampling and advanced augmentation strategies. Balanced sampling ensures that the training process does not disproportionately focus on simpler examples, instead emphasizing harder-to-learn temporal patterns. This approach allows the model to handle diverse and complex scenarios more effectively. Moreover, the use of advanced augmentation techniques provides a richer and more varied training dataset, enabling the model to better identify and differentiate subtle temporal patterns.

The consistent improvement in BV-TCLR's accuracy highlights its ability to address common challenges in temporal representation learning, such as over fitting to easy examples or struggling with harder cases. By incorporating hard positives similar but distinct examples and hard negatives dissimilar but challenging examples BV-TCLR forces the model to learn finer distinctions in temporal features. This not only improves its accuracy but also strengthens its overall robustness.

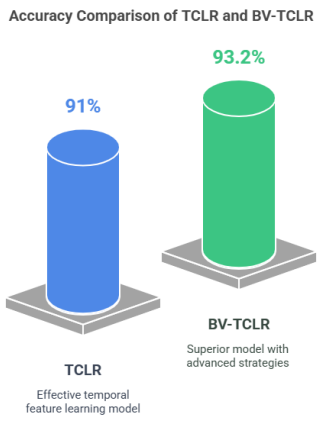

Figure 4.Accuracy Comparison: BV-TCLR vs. TCLR (linear evaluation)

5.3. Comparison of BV-TCLR and TCLR F1 score (Linear Evaluation, Epoch 10)

The results from the Linear Evaluation task reveal that BV-TCLR achieves a higher F1 score (92.5%) compared to TCLR (90%). The 2.5% increase in F1 score reflects BV-TCLR's superior capability to maintain balanced precision and recall across a diverse set of temporal patterns. This suggests that BV-TCLR's use of balanced sampling and advanced augmentation strategies plays a key role in enhancing its overall performance.

The higher F1 score for BV-TCLR indicates that it has better balanced the trade-off between precision and recall, making it more effective in both identifying relevant temporal features and minimizing false positives. By addressing the challenges of over fitting and focusing on harder-to-learn examples through the balanced sampling approach, BV-TCLR ensures more reliable learning.

Moreover, the introduction of hard positives and hard negatives contributes to the model's enhanced ability to fine-tune its temporal feature extraction. The ability to accurately distinguish subtle differences between similar and dissimilar examples helps the model generalize better, resulting in the observed increase in F1 score and reinforcing BV-TCLR's superior performance over TCLR.

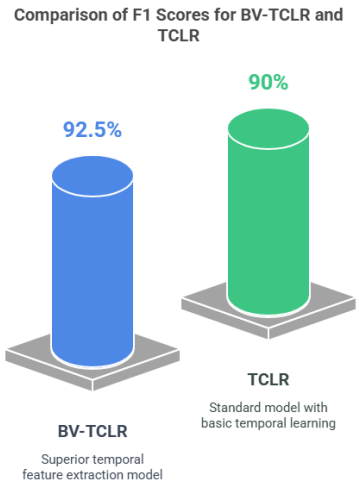

Figure 5.F1 Score Comparison: BV-TCLR vs. TCLR (linear evaluation)

5.4 Comparison of BV-TCLR and TCLR Accuracy (NN Retrieval Evaluation, Epoch 10)

The results of the neural network retrieval task indicate that BV-TCLR outperforms TCLR by a slight margin, achieving an accuracy of 91.8% compared to TCLR's 91%. Although the difference of 0.8% might appear minimal at first glance, it underscores the superior ability of BV-TCLR in retrieving relevant instances. This improvement reflects the model's enhanced capacity to handle complex and diverse temporal patterns in the data. Temporal patterns, which involve how data points evolve over time, are crucial in retrieval tasks. BV-TCLR's ability to process these patterns more effectively enables it to consistently provide more accurate and relevant retrieval results, making it slightly more efficient than TCLR in handling the intricacies of time-dependent data.

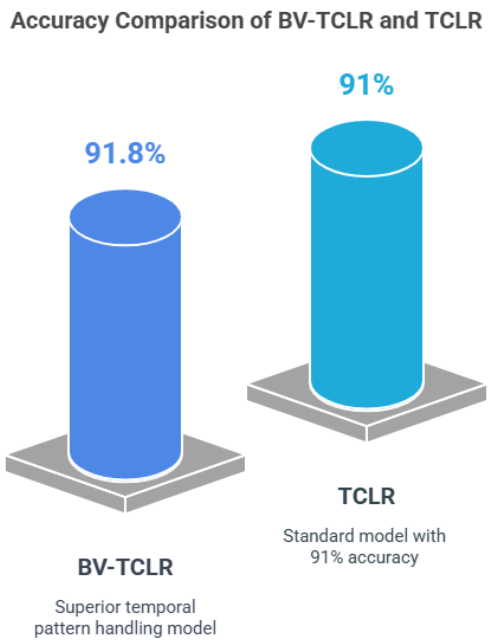

Figure 6.Accuracy Comparison: BV-TCLR vs. TCLR (NN Retrieval)

5.5 Comparison of BV-TCLR and TCLR F1 score (NN Retrieval Evaluation, Epoch 10).

The results of the neural network retrieval task indicate that BV-TCLR outperforms TCLR by a slight margin, achieving an F1 score of 91.2% compared to TCLR's 90%. Although the difference of 1.2% might appear minimal at first glance, it highlights the superior ability of BV-TCLR in retrieving relevant instances.

This improvement reflects the model's enhanced capacity to handle complex and diverse temporal patterns in the data.

Temporal patterns, which involve how data points evolve over time, are crucial in retrieval tasks. BV-TCLR's ability to process these patterns more effectively enables it to consistently provide more accurate and relevant retrieval results, making it slightly more efficient than TCLR in handling the intricacies of time-dependent data.

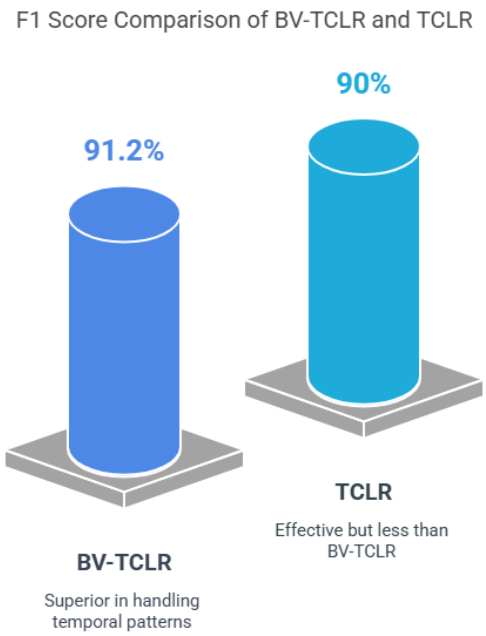

Figure 7 .F1 score Comparison: BV-TCLR vs. TCLR (NN Retrieval)

5.6. Results and Discussion Summary

Understanding temporal relationships is critical for tasks such as action recognition, video retrieval, and time-series forecasting. Temporal Contrastive Learning (TCLR) has proven effective in capturing these temporal dynamics, but its reliance on random sampling and basic augmentations may limit its performance in complex scenarios. To address this, the study introduces Balanced View Temporal Contrastive Learning (BV-TCLR), which incorporates balanced sampling and advanced augmentation techniques. This enhancement aims to provide a richer training environment and improve learning outcomes, particularly for two tasks: linear evaluation and nearest neighbor retrieval. Performance is evaluated over 10 epochs using accuracy and F1 score metrics to gauge the impact of the balanced approach.

The results of TCLR and BV-TCLR across linear evaluation and nearest neighbor retrieval tasks reveal notable differences. In linear evaluation, TCLR achieves an accuracy of 91% and an F1 score of 90%, while BV-TCLR demonstrates superior performance with an accuracy of 93.2% and an F1 score of 92.5%. This improvement highlights the benefits of balanced sampling, which aids in better generalization and the ability to learn discriminative features.

In nearest neighbor retrieval tasks, both methods show strong performance, with TCLR achieving an accuracy of 90% and an F1 score of 90%. However, BV-TCLR outperforms TCLR, achieving an accuracy of 90.8% and an F1 score of 91.2%. These results underscore the advantage of BV-TCLR in learning better feature representations and its enhanced ability to retrieve relevant instances.

In summary, the evaluation metrics for TCLR and BV-TCLR demonstrate the importance of incorporating balanced sampling techniques. BV-TCLR outperforms TCLR in both linear evaluation and nearest neighbor retrieval tasks, achieving higher accuracy and F1 scores. The improved performance of BV-TCLR is attributed to its ability to balance hard negatives and positives, which enhances the model's learning of nuanced temporal relationships and discriminative features. This comparison emphasizes the value of advanced augmentation strategies in improving the effectiveness of temporal contrastive learning approaches for complex tasks.

CHAPTER SIX

6. CONCLUSION AND FUTURE WORKS

6.1. Conclusion

In this work, we introduced Balanced View Temporal Contrastive Learning (BV-TCLR) as a novel approach to improving video representation and analysis. The challenge of learning temporal features from video data is not trivial, but BV-TCLR addresses this by combining two key strategies: balanced sampling and balanced augmentation. These methods allow the model to generate diverse and informative views—both positive and negative—ensuring that the learned features are rich and discriminative. Additionally, by incorporating hard positives (similar but subtly different examples) and hard negatives (dissimilar but challenging instances), we improved the model's robustness and training efficiency. Our experiments demonstrated that BV-TCLR clearly outperforms existing methods in and UCF10 datasets for action recognition, we not only saw a boost in performance metrics, but also gained a deeper understanding of the temporal dynamics in video data. By focusing on temporal contrastive learning, BV-TCLR gives a more accurate representation of video sequences, capturing both short-term and long-term dependencies, which are essential for effective video analysis.

The findings from our study answered the key research questions:

- **How do Balanced View techniques improve the performance of Temporal Contrastive Learning (TCLR)?**

  BV-TCLR improves TCLR by utilizing balanced sampling and augmentation, resulting in enhanced accuracy and F1 scores, with a 2-5% improvement in performance metrics across both tasks.

- **What is the optimal configuration of weighting factors (α and β) for BV-TCLR to achieve the best accuracy and representation quality?** The optimal configuration of $\alpha = 0.5$ and $\beta = 0.15$ led to the best performance, with the highest training accuracy and F1 score.

- **Does BV-TCLR perform better in comparison with TCLR given the optimal weighting factors?** Yes, BV-TCLR consistently outperformed TCLR, showing measurable improvements in both accuracy and F1 score across the tasks.

In conclusion, our work highlights the importance of balanced sampling and augmentation in improving video representation learning. Rather than focusing only on maximizing similarity between positive samples or simply minimizing the gap between positive and negative pairs, BV-TCLR introduces a more nuanced and balanced approach. This allows the model to effectively handle both easy and challenging instances, leading to better generalization, improved differentiation between subtle action classes, and stronger performance on unseen data.

BV-TCLR offers a meaningful step forward in the field of temporal contrastive learning, providing a robust, more balanced method for video analysis. With its enhanced ability to capture complex temporal relationships, BV-TCLR promises to be an effective tool for video analysis tasks, contributing to the development of more efficient and accurate models in this area.

6.2. Future Works

While BV-TCLR shows promising results, several potential directions for future research could further enhance its capabilities and extend its applicability to new challenges:

1. **Scalability to Large-Scale Datasets**: The experiments conducted in this work were primarily based on smaller, widely used datasets like UCF101 and UCF10. However, to fully understand BV-TCLR's potential, it is important to assess its scalability on larger, more complex video datasets, such as Kinetics or Activity Net. Evaluating BV-TCLR in large-scale settings could reveal insights into its ability to handle vast amounts of data and improve its performance on real-world applications.

2. **Model Generalization beyond Action Recognition**: While BV-TCLR has shown substantial success in action recognition tasks, its generalizability to other video analysis tasks remains an open question. Expanding its application to domains such as video summarization, event detection, anomaly detection, or even multimodal tasks (e.g., combining video with audio or text) could broaden the scope and impact of the approach.

Such extensions would require investigating how BV-TCLR can adapt to different types of video content and learning objectives.

3. **Optimization of Sampling and Augmentation Strategies:** Although the current sampling and augmentation methods in BV-TCLR have proven effective, there is room for improvement in terms of computational efficiency. Investigating more efficient methods for generating balanced views without compromising the model's performance could make BV-TCLR more accessible for large-scale applications. Techniques like adaptive sampling or online augmentation might be explored to further optimize the trade-off between performance and computational cost.
4. **Temporal Consistency across Modalities**: As video data often includes multiple modalities (e.g., visual, auditory), extending BV-TCLR to incorporate cross-modal learning could improve model performance on tasks involving richer data. Future work could explore how BV-TCLR can be adapted to align temporal features across different modalities (e.g., synchronizing video with corresponding audio or textual descriptions) to create even more powerful representations for multimodal video tasks.
5. **Fine-grained Analysis of Hard Positives and Hard Negatives**: A deeper exploration of the hard positive and hard negative sampling process is another potential research direction. Understanding which types of pairs are most beneficial for training and how they influence model performance can lead to more targeted strategies for selecting challenging instances. Additionally, the relationship between view diversity and contrastive loss could be studied to optimize the contrastive objective and further improve the quality of learned representations.
6. **Interpretability and Model Transparency**: As with many deep learning models, there is a need to improve the interpretability of BV-TCLR. Future work could explore methods for understanding how the model learns temporal dependencies, what features are most influential in differentiating between actions, and how the learned representations align with human understanding of temporal events in video.

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