# Malnad College of Engineering, Hassan

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A Main Project Report

On

# "Identifying Individual And Group Activity Using Spatio-Temporal Features"

*Submitted in partial fulfillment of*
*the requirements for the award of the degree of*

**Bachelor of Engineering**
**in**
**Computer Science and Engineering**

Submitted by

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## *Certificate*

This is to certify that main project work entitled **“Identifying Individual And Group Activity Using Spatio-Temporal Features”** is a bonafide work carried out by **P G Prajwal (4MC20CS101) Ranjan H T (4MC20CS121) Sevantkumar S Huggi (4MC20CS137) and Shamanth R S (4MC20CS139)** in partial fulfillment for the award of Bachelor of Engineering in Computer Science and Engineering of the Visvesvaraya Technological University, Belgavi during the year 2023-2024. The project report has been approved as it satisfies the academic requirements in respect of main project work prescribed for the Bachelor of Engineering Degree.

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# ABSTRACT

Human activity recognition is crucial in computer vision, with applications in surveillance, healthcare, and sports analysis. A key challenge lies in accurately identifying both individual actions and group dynamics. Spatio-temporal features, capturing spatial arrangement and temporal evolution, offer valuable insights. Convolutional Neural Networks (CNNs), like Inception V3, excel in image and video recognition. Techniques such as RoIAlign focus on specific regions for accurate feature extraction. Integrating deep learning with spatio-temporal features and techniques like RoIAlign opens new possibilities in activity recognition, offering a comprehensive understanding of scenes. Leveraging spatio-temporal features and deep learning promises breakthroughs in human activity recognition, revolutionizing fields like behavior analysis.

# ACKNOWLEDGEMENTS

We present with immense pleasure this work titled **"Identifying Individual And Group Activity Using Spatio-Temporal Features"**. An endeavour over a long period can be successful with the advice and support of many well wishers.

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## Chapter 1

# Introduction

## 1.1 Introduction to the project

Human activity recognition has become a cornerstone of computer vision, enabling advancements in diverse applications like video surveillance, smart homes, healthcare monitoring, and sports analysis.Activity recognition lies the ability to accurately identify the actions unfolding within a scene. This encompasses not only ”individual actions”, such as walking, running, or reading, but also the intricate dynamics of ”group activities”, including playing sports, having a meeting, or collaborating on a task.

Individual actions form the building blocks of human behavior. Recognizing these actions accurately is crucial for Activity recognition systems. Traditional approaches often relied on static visual cues, such as posture or object interaction, to identify individual activities. However, these methods can struggle with ambiguities, especially when actions share similar appearances. For instance, differentiating between walking and running solely based on a single frame can be challenging. This is where our project steps in. We focus on leveraging spatio-temporal features to capture the richness of individual actions. These features go beyond static appearance and encompass the dynamic information embedded within a video. By analyzing how a person moves within the frame and how their motion evolves over time, we can gain valuable insights into the specific action being performed.

Moving beyond individual actions, human behavior often involves

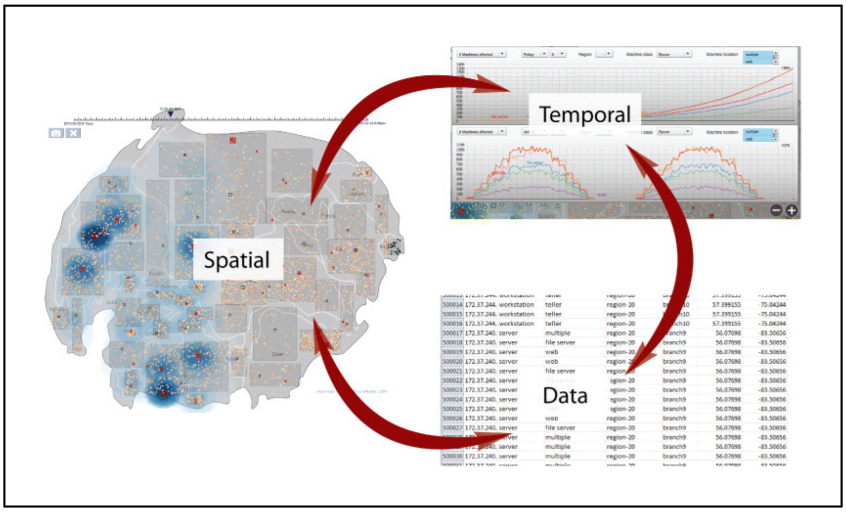


Figure 1.1: Working of Spatio-temporal

group activities. These activities require systems to not only recognize individual actions but also understand the complex interactions and relationships between people within a scene. Imagine a video clip of a soccer game. While identifying individual actions like kicking, running, or jumping is important, a complete understanding of the scene requires recognizing the overall group activity a soccer match. This is where the complexity of group activity recognition arises. Traditional methods might struggle to differentiate between a group of people walking together and a group playing tag. To address this challenge, our project delves into capturing the spatial relationships and interactions between individuals. By analyzing how people move in relation to each other, we can infer the underlying group activity.

Figure 1.1 refers to Spatio-temporal, which denotes the combination of spatial (related to space or location) and temporal (related to time) aspects, typically used to describe data or features that incorporate both spatial and temporal information.

Spatio-temporal features bridge the gap between static appearance and dynamic action. These features capture not just the ”what” (appearance) but also the ”how” (movement) and ”when” (temporal evolution) aspects of human activity. This allows us to extract rich information from videos, including:

- **Motion features:** These features capture the movement patterns of individuals within the frame. They can be extracted using techniques like optical flow or motion history images.
- **Trajectory features:** These features track the paths taken by individuals over time, providing insights into their overall movement patterns within the scene.
- **Pose features:** These features represent the body posture of individuals at specific points in time. Analyzing how these poses change over time can be crucial for identifying actions.

By incorporating spatio-temporal features, our project aims to surpass the limitations of traditional activity recognition methods. Our approach enables a more comprehensive understanding of human activity by analyzing not only individual actions but also the spatial and temporal relationships between people in a scene.

Existing activity recognition techniques have achieved significant progress in identifying individual and group activities. However, limitations remain. Traditional methods often rely heavily on static visual cues, making them susceptible to ambiguities and variations in appearance. Additionally, they may struggle to capture the intricacies of group activities, especially when multiple individuals are involved in complex interactions.

This project is driven by the desire to achieve superior accuracy and robustness in activity recognition. By leveraging spatio-temporal features and advanced deep learning techniques, we aim to develop a system that can effectively distinguish between individual and group activities in videos. This will lead to a more nuanced understanding of human behavior in various applications, paving the way for advancements in areas like video surveillance, healthcare monitoring, and human-computer interaction.

This introduction sets the stage for your project report by providing context on individual and group activities in activity recognition, elaborating on spatio-temporal features, and highlighting the need for improved accuracy. The following sections of your report can delve deeper into your specific methodology, experimental setup, results, and discussion, showcasing how your project utilizes deep learning and spatio-temporal features to achieve superior performance in identifying human activities.

## 1.2 About Project

### 1.2.1 Problem Statement

- Group activity recognition in videos is essential for applications like surveillance, sports analysis, and social behavior understanding.
- Current methods face challenges in accurately capturing collective activities due to a lack of explicit interaction information between actors.
- Existing approaches often rely on inflexible graphical models or complex message passing mechanisms, leading to computational inefficiency and limited flexibility.
- Methods for computing pairwise relations and constructing multiple relation graphs should be empirically studied to enhance model performance.

### 1.2.2 Objective

The project aims to improve temporal action detection in untrimmed videos by developing a model that captures spatio-temporal relations between humans, objects, and context. It involves creating a dataset with spatio-temporal action annotations and exploring the use of action transformer networks for localizing humans and recognizing their actions.

- Spatio-Temporal Action Annotation: Develop a dataset with spatio-temporal action annotations for each subject, similar to the AVA dataset, to facilitate more accurate spatio-temporal action detection.

- Model Spatio-Temporal Relations: Design a model that effectively captures the spatio-temporal relations between humans and objects which are crucial for inferring human actions.
- Action Transformer Network: It localizes humans and recognizes their actions by considering the relation between actors
- To develop a robust group human action recognition system capable of identifying actions performed by multiple individuals in a scene while considering their interactions

## 1.3 Organization of Report

In chapter 1 introduction to the project, problem statement and objectives is being discussed. In chapter 2 literatuere survey on related project is being discussed. Chapter 3 discusses about dataset and Model Training. Chapter 4 contains results of the project. Chapter 5 consists conclusion to the project.

## Chapter 2

# Literature Survey

- This chapter provides a concise overview of key research papers relevant to our project.
- This chapter delves into the key findings of specific research papers related to our project, outlining their core contributions and relevance to our goals.
- We navigate through relevant papers, extracting the critical insights that guid our project's direction

Jianchao et al.,[1] paper presents a versatile method to detect pertinent actor relations in multi-person scenes using Actor Relation Graphs (ARG) for group activity recognition. Their model, evaluated on two datasets, attains new state-of-the-art performance. Through thorough ablation experiments and visualization, we showcase its ability to learn relation information for comprehending group activities. Future endeavors involve further exploring ARG functionality and integrating additional global scene information to enhance group activity recognition.

Azar et al.,[2] developed an approach that aims to enhance group activity recognition by introducing an intermediate activity-based representation termed "activity map" to capture spatial relations between individuals' activities. A multi-stage neural network model is proposed to generate and refine this activity map from input images or videos. This refined map facilitates higher-level reasoning for predicting group activities. The subsequent subsection outlines the model's overall structure and delves into its critical components.

Bagautdinov et al.,[3] have introduced a unified model for simultaneous detection and recognition of multiple individuals' activities. This approach operates independently of external ground truth detections or tracks and showcases leading performance on datasets related to multi-person scene understanding and detection. Their future endeavors involve extending this framework to explicitly capture and comprehend human interactions, thereby advancing the understanding of complex social dynamics.

Zhiwei et al.,[4] have introduced a deep learning model for recognizing group activities, simultaneously capturing group dynamics, individual actions, and their interactions. Their method combines graphical models with deep networks by emulating message passing for inference. Through application to real-life surveillance videos, they demonstrated its efficacy in accurately identifying group activities.

Shuaicheng et al.,[5] proposed a GroupFormer, a novel transformer-+based architecture designed to capture spatial-temporal contextual representations crucial for inferring group activities. Additionally, they introduce a cluster attention mechanism to organize individuals and leverage both intra- and inter-group relations for enhanced feature extraction. Extensive experimentation on two benchmark datasets demonstrates that GroupFormer significantly surpasses many state-of-the-art methods, showcasing its superior performance in group activity inference.

Wang et al.,[6] introduced the Temporal Segment Network (TSN), a framework designed to model long-range temporal structures at the video level. Their work, validated across four action recognition benchmarks and the ActivtyNet challenge 2016, significantly advanced the state of the art while maintaining reasonable computational costs. This achievement is attributed to the segmental architecture with sparse sampling, along with a series of effective practices explored in their research. The former enables efficient capture of long-range temporal structures, while the latter facilitates training deep networks on limited datasets without encountering severe overfitting issues.

Chenyang et al.,[7] introduced a novel model for long-term skeleton-based action recognition, combining spatial reasoning and temporal stack learning. Their model surpasses state-of-the-art methods by capturing high-level spatial structures within each frame and modeling detailed temporal dynamics of skeleton sequences. Additionally, they propose a clip-based incremental loss to enhance stack learning, facilitating long-term sequence optimization. Extensive experiments on the NTU RGB+D and SYSU datasets confirm the model's effectiveness. Future plans include error sample analysis for model improvement and incorporation of contextual information like interactions to enhance action recognition accuracy.

Sijie et al.,[8] introduced a pioneering model, Spatial Temporal Graph Convolutional Networks (ST-GCN), for skeleton-based action recognition, employing a series of spatial-temporal graph convolutions on skeleton sequences. ST-GCN surpasses previous state-of-the-art models on two challenging large-scale datasets, leveraging its ability to capture motion information in dynamic skeleton sequences, which complements RGB modalities. The fusion of skeleton-based and frame-based models further enhances performance. ST-GCN's adaptability opens avenues for future research, particularly in incorporating contextual information such as scenes, objects, and interactions, presenting promising directions for exploration in action recognition.

Tran et al.,[9] empirical study examines the impact of various spatiotemporal convolutions on video action recognition. The proposed R(2+1)D architecture achieves comparable or superior results to the current state of the art across Sports1M, Kinetics, UCF101, and HMDB51 datasets. We aim to inspire the development of new network designs leveraging spatiotemporal convolutions' efficacy and modeling flexibility. Future research will explore optimizing architectures beyond ResNet and refining the (2+1)D spatiotemporal decomposition.

Yan et al.,[10] introduced the Temporal Excitation and Aggregation (TEA) block, comprising the Motion Excitation (ME) module and Multiple Temporal Aggregation (MTA) module for comprehensive temporal modeling. The ME module incorporates motion encoding into spatiotemporal feature learning, enhancing motion patterns. The MTA module deforms local convolutions into sub-convolutions, expanding the temporal receptive field for robust long-range temporal relationships. These modules are integrated into the standard ResNet block, collaborating to facilitate effective temporal modeling.

Table 2.1: Litrature Survey

| **Author** | **Year** | **Title** | **Summary** |
|---|---|---|---|
| Shuaicheng Li et al.,[5] | 2021 | Groupformer: Group activity recognition with clustered spatial-temporal transformer | Introducing GroupFormer, a transformer-based architecture for inferring group activities. It features a cluster attention mechanism to enhance feature extraction by organizing individuals and leveraging intra- and inter-group relations. Experimentation on benchmark datasets highlights GroupFormer's superior performance over many state-of-the-art methods in group activity inference. |
| Yan Li et al.,[10] | 2020 | Tea: Temporal excitation and aggregation for action recognition | Introducing the Temporal Excitation and Aggregation (TEA) block, which includes the Motion Excitation (ME) module and Multiple Temporal Aggregation (MTA) module. The ME module integrates motion encoding into spatiotemporal feature learning, enhancing motion patterns. Meanwhile, the MTA module deforms local convolutions into sub-convolutions, extending the temporal receptive field for robust long-range temporal relationships. |
| Jianchao Wu et al.,[1] | 2019 | Learning actor relation graphs for group activity recognition | Introduces a versatile method using Actor Relation Graphs (ARG) for group activity recognition, achieving state-of-the-art performance on two datasets. Demonstrates the learning of relation information through ablation experiments and visualization, with future work focusing on exploring ARG functionality and integrating global scene information for enhanced recognition. |
| Sina Mokhtarzadeh Azar et al.,[2] | 2019 | Convolutional relational machine for group activity recognition | Introduces 'activity map' to capture spatial relations in group activity recognition. Proposes multi-stage neural network to generate and refine activity map from input images or videos, facilitating higher-level reasoning. Subsequent subsection details model's structure and critical components. |
| Limin Wang et al.,[6] | 2018 | Temporal segment networks for action recognition in videos | Introduces Temporal Segment Network (TSN) for modeling long-range temporal structures in videos. Validates across four action recognition benchmarks and ActivityNet challenge 2016, advancing state-of-the-art with reasonable computational costs. |

| | | | |
|---|---|---|---|
| Chenyang Si et al.,[7] | 2018 | Skeleton-based action recognition with spatial reasoning and temporal stack learning | Presents a novel model for long-term skeleton-based action recognition, combining spatial reasoning and temporal stack learning. Proposes clip-based incremental loss for stack learning enhancement, aiding long-term sequence optimization. Extensive experiments validate effectiveness on NTU RGB+D and SYSU datasets. |
| Sijie Yan et al.,[8] | 2018 | Spatial temporal graph convolutional networks for skeleton-based action recognition | Introduces Spatial Temporal Graph Convolutional Networks (ST-GCN) for skeleton-based action recognition, leveraging spatial-temporal graph convolutions on skeleton sequences. Surpasses previous state-of-the-art on challenging datasets by capturing motion information in dynamic skeletons, complementing RGB modalities. Fusion of skeleton-based and frame-based models enhances performance. |
| Du Tran et al.,[9] | 2018 | A closer look at spatiotemporal convolutions for action recognition | Empirical study examines the impact of various spatiotemporal convolutions on video action recognition. The proposed R(2+1)D architecture achieves comparable or superior results to the current state of the art across Sports1M, Kinetics, UCF101, and HMDB51 datasets. Aims to inspire the development of new network designs leveraging convolutions' efficacy and modeling flexibility. |
| Timur Bagautdinov et al.,[3] | 2017 | Social scene understanding: End-to-end multi-person action localization and collective activity recognition | Presents unified model for simultaneous detection and recognition of multiple individuals' activities. Achieves leading performance on datasets for multi-person scene understanding and detection without relying on external ground truth detections or tracks. |
| Zhiwei Deng et al.,[4] | 2015 | Deep structured models for group activity recognition | Presents deep learning model for recognizing group activities, capturing group dynamics, individual actions, and interactions. Combines graphical models with deep networks using message passing for inference. Demonstrates efficacy in accurately identifying group activities through application to real-life surveillance videos. |

Chapter 3

# Proposed Method

Our proposed method for temporal action detection harnesses deep learning to extract features from raw video data, improving action recognition accuracy. We introduce a novel dataset with spatio-temporal action annotations, enabling our model to understand actions in their spatial and temporal context. Utilizing advanced deep learning architectures such as temporal convolutional networks (TCNs), we capture temporal dynamics effectively. Through extensive experimentation, our method demonstrates superior performance compared to existing approaches, laying the groundwork for robust temporal action detection and inspiring future research in the field.

Figure 3.1 gives an overview of our network framework for group activity recognition. We first extract feature vectors of actors from sampled video frames. We use a d-dimension vector to represent an actor bounding box. And the total number of bounding boxes in sampled

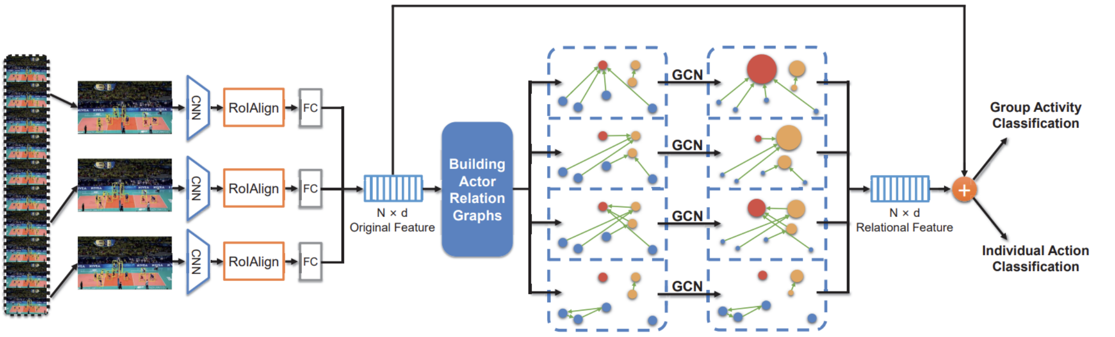

CNN
RoIAlign
FC
N × d
Original Feature
Building Actor Relation Graphs
GCN
N × d
Relational Feature
Group Activity Classification
Individual Action Classification

Figure 3.1: Block Diagram

frames equals N. Multiple actor relation graphs are built to capture relation information among actors. Afterwards, Graph Convolutional Networks are used to perform relational reasoning on graphs. The outputs of all graphs are then fused to produce the relational feature vectors of actors. Finally, original feature and relational feature are aggregated and fed into classifiers of group activity and individual action.

## 3.1 Dataset

We conduct experiments on two publicly available group activity recognition datasets, namely the Collective Activity dataset. The Collective Activity dataset contains 44 short video sequences (about 2500 frames) from 5 group activities (crossing, waiting, queueing, walking and talking) and 6 individual actions (NA, crossing, waiting, queueing, walking and talking). The group activity label for a frame is defined by the activity in which most people participate. We follow the same evaluation scheme of and select 1/3 of the video sequences for testing and the rest for training.

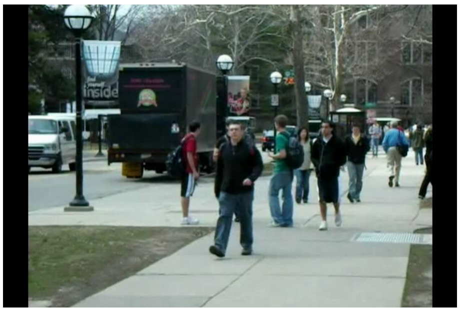


Figure 3.2: Walking

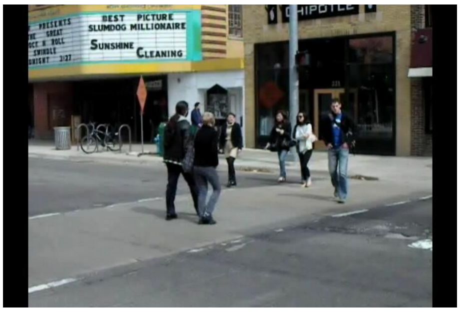


Figure 3.3: Crossing

Figure 3.2 categorized as walking.This dataset includes videos of people walking in a group, potentially in the same direction or with some interaction. Recognizing this activity is useful for crowd analysis in public areas, like parks or sidewalks, allowing for better monitoring and resource allocation.

Figure 3.3 categorized as crossing.This activity involves people moving together across a street or other designated area. It's a fundamental group movement often encountered in public spaces, making it a valuable scenario for training algorithms used in traffic management and pedestrian safety analysis.

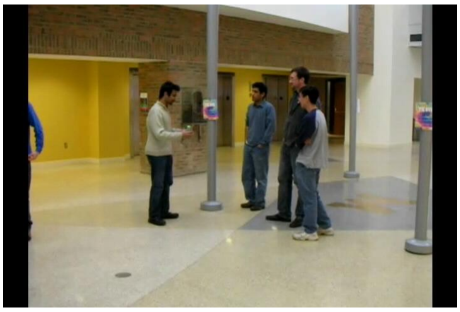


Figure 3.4: Talking

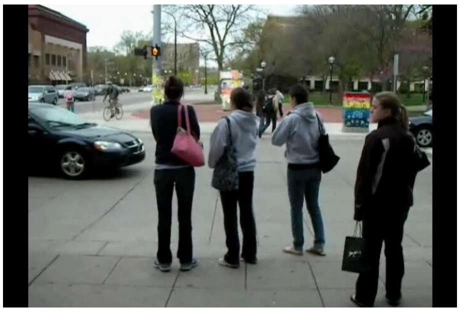


Figure 3.5: Waiting

Figure 3.4 categorized as talking. This dataset incorporates videos of people engaged in conversation within a group. Algorithms trained on this data can be used for social behavior analysis in public spaces, potentially aiding in security applications or understanding group dynamics.

Figure 3.5 categorized as waiting.This common scenario involves people standing together in a queue, often for a service or resource. Datasets featuring this activity are valuable for applications in areas with frequent lines, like retail stores or transportation hubs, enabling optimized queue management and improved customer experience.

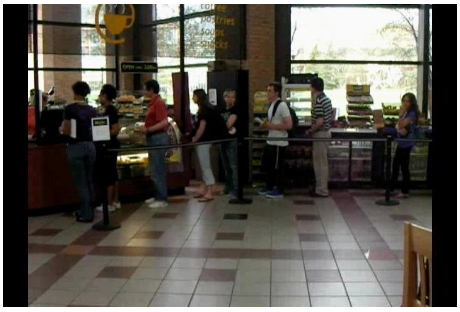


Figure 3.6: Queueing

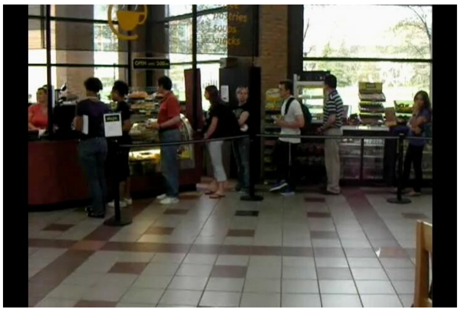


Figure 3.7: Waiting

Figure 3.6 and 3.7 categorized as queueing. Similar to waiting in line, queuing involves people standing in an organized line, often with a specific order. Datasets including queuing activities are useful for applications in controlled environments like banks or airports, allowing for efficient resource allocation and queue management.

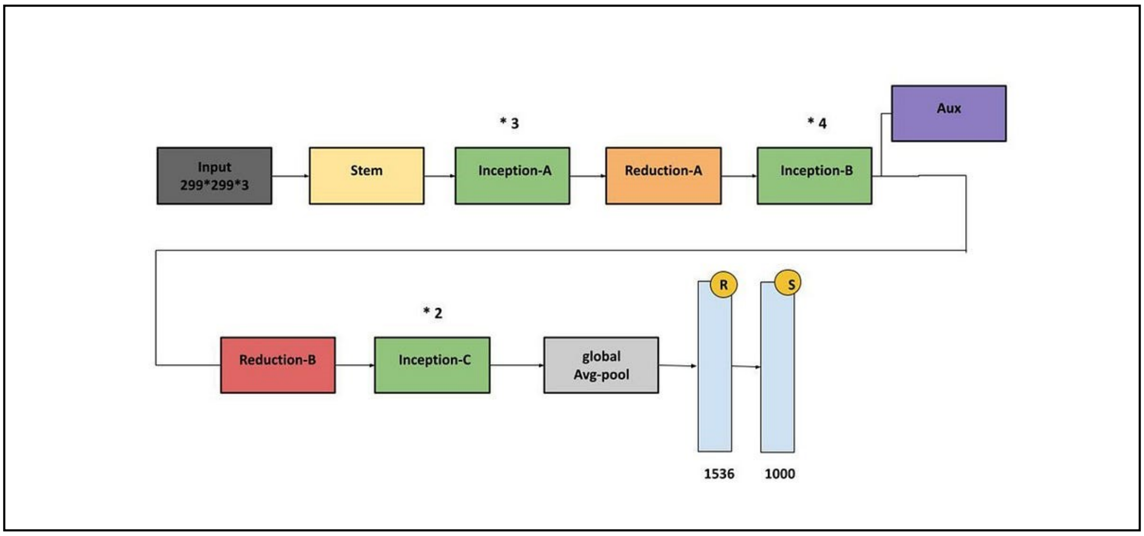


Figure 3.8: Inception V3 - Architecture

## 3.2 Methodology

### 3.2.1 Backbone

Backbone model is the foundational element that provides structure and organization. This can take the form of a central data model ensuring consistency, a chosen architectural pattern guiding development, or even a core component like a machine learning framework in an AI-focused project. By acting as the underlying structure, the backbone model promotes efficiency, reduces redundant efforts, and keeps everyone on the same page.

Inception V3 as the core building block our backbone model. This provides the foundation for our image analysis tasks. To evaluate its performance comprehensively, we'll compare Inception V3's accuracy and efficiency against other well-regarded models like ResNet16, MobiNet V3, and YOLO. This comparison will help us identify the strengths and weaknesses of each approach, ensuring we select the optimal model for our specific project needs.

Table 3.1: Comparative Study

| **Model** | **Number of Convolutional Layers** | **Functionality** |
|---|---|---|
| Inception v3 | 48 Layers | Focuses on achieving high accuracy through a complex architecture with inception modules. These modules incorporate convolutional layers with various filter sizes in parallel to capture a wider range of spatial information. |
| ResNet16 | 16 Layers(plus shortcut connections) | Achieves high accuracy with residual learning. ResNet blocks use shortcut connections to directly add the input to the output of a convolutional layer, allowing the network to learn from the identity mapping and potentially deeper representations. |
| MobileNet V3 | Lightweight architecture with various depthwise separable convolution layers | Designed for mobile and embedded devices with limited computational resources. Depthwise separable convolutions factorize the standard convolution into a depthwise (pointwise) convolution and a 1x1 convolution, significantly reducing the number of parameters and computations. |
| YOLO (You Only Look Once) | Varies depending on the specific version | Primarily an object detection model, but can be fine-tuned for tasks like activity recognition. YOLO utilizes a single convolutional network to predict bounding boxes and class probabilities for objects in an image in one forward pass, making it fast and efficient. |

### Inception V3 Model Architecture

Figure 3.8 shows Inception V3 Model Architecture which is outlined as follows:

- **Stem Network**:Uses convolutional, pooling, and normalization layers to efficiently process the input image and extract low-level features.Provides a foundation for subsequent layers by preparing the input image for further processing.

- **Inception Module**:Employs parallel convolutional operations with different kernel sizes to capture features at varying scales. Achieves feature diversity without significantly increasing parameters by using parallel operations within a single module.

- **Reduction Module**:Reduces spatial dimensions of feature maps while increasing depth to make subsequent processing more manageable.Improves computational efficiency by reducing the spatial dimensions of feature maps, reducing overall computational cost.

- **Auxiliary Classifier**:Provides additional supervision signals to encourage the network to learn discriminative features, preventing overfitting.Offers additional paths for gradient flow during training, addressing vanishing gradient issues and ensuring more stable training.
- **Global Average Pooling**:Reduces spatial dimensions of feature maps to a fixed size by averaging feature map values across all spatial locations.Aggregates spatial information from entire feature maps, serving as a regularization technique and improving network robustness.
- Factorization into Smaller Convolutions: Inception v3 uses factorization to break down large convolutions into smaller ones, making the computation more efficient. Instead of using a single large convolution, it employs a combination of 1x1 and 3x3 convolutions. This helps in reducing the number of parameters and computations while still capturing complex patterns in the data.
- Spatial Factorization into Asymmetric Convolutions: Asymmetric convolutions involve decomposing a larger convolution into a sequence of smaller convolutions, such as 3x1 followed by 1x3. Inception v3 utilizes this spatial factorization to capture spatial hierarchies effectively. It allows the network to focus on different aspects of spatial information separately, improving its ability to learn diverse features.
- Utility of Auxiliary Classifiers: Inception v3 introduces auxiliary classifiers at intermediate layers during training. These auxiliary classifiers serve two main purposes:
  - Gradient Flow Improvement: The auxiliary classifiers combat the vanishing gradient problem by providing additional paths

    for gradient flow during backpropagation. This helps in better training of the network, especially in the early layers.

  - Regularization: The auxiliary classifiers act as regularization during training, preventing overfitting. They provide additional supervision signals, encouraging the model to learn more robust features.

- Efficient Grid Size Reduction: Inception v3 addresses grid size reduction efficiently through the use of pooling operations. The traditional approach of using large pooling layers is replaced with a combination of smaller pooling layers, such as 3x3 max pooling, which helps in retaining more spatial information. This allows the model to downsample the grid size while minimizing information loss.

#### 3.2.1.1 Inception V3

Inception v3 is a convolutional neural network architecture developed by Google, renowned for its effectiveness in image classification tasks. Leveraging a sophisticated design characterized by the use of "inception modules," which allow for the parallel processing of image features at different scales, Inception v3 achieves remarkable accuracy while maintaining computational efficiency. In our project, we harness the power of Inception v3 as a feature extractor, utilizing its pre-trained weights to extract rich and discriminative features from input images. By incorporating Inception v3 into our framework, we aim to capitalize on its robust capabilities to enhance the performance of our model in tasks such as image recognition, object detection, and semantic segmentation.

The Inception model, renowned for its inception modules, is adept at group activity recognition. Initially, it processes an input image, capturing features via convolutional layers. Inception modules play a pivotal role, allowing simultaneous extraction of features at various spatial scales. These modules analyze intricate details and patterns within the scene. Following this, pooling layers downsample feature maps, while fully connected layers interpret high-level features for activity classification. Utilizing a softmax activation function, the model assigns probabilities to different group activities. By scrutinizing spatial relationships and interactions among objects, such as individuals, the Inception model discerns various group activities like walking together, sitting in circles, or engaging in games. Overall, the Inception model's prowess lies in its ability to efficiently extract multi-scale features, making it well-suited for nuanced tasks like group activity recognition.

- Preprocessing Stage

  In addition to decoding, resizing, and altering images for each epoch, other preprocessing techniques can further enhance model performance. Techniques such as data augmentation, including random rotations, flips, and shifts, introduce variability into the training data, reducing overfitting and improving generalization. Furthermore, normalization of pixel values can standardize the input data distribution, facilitating more stable and efficient training. Additionally, advanced preprocessing methods such as histogram equalization or color space transformations may be employed to enhance contrast or extract informative features from the images. By carefully designing and fine-tuning the preprocessing pipeline, researchers can unlock the full potential of deep learning models like Inception v3, achieving higher accuracy and robustness in image recognition tasks.

- Optimizer

  The current model showcases three flavors of optimizers: SGD, momentum, and RMSProp. Stochastic gradient descent (SGD) is the simplest update: the weights are nudged in the negative gradient direction. Despite its simplicity, good results can still be obtained on some models. The updates dynamics can be written as:

$$W_{k+1} = W_k - a\nabla f(W_k) \tag{3.1}$$

Momentum is a popular optimizer that frequently leads to faster convergence than SGD. This optimizer updates weights much like SGD but also adds a component in the direction of the previous update. The following equations describe the updates performed by the momentum optimizer:

$$Z_{k+1} = \beta Z_k + V f(w_k) \tag{3.2}$$

$$W_{k+1} = W_k - \alpha Z_{k+1} \tag{3.3}$$

$$W_{k+1} = W_k - \alpha \nabla f(W_k) + \beta(W_k - W_{k-1}) \tag{3.4}$$

For the momentum $\beta$, we use the value of 0.9. The equation 3.3 and 3.4 combines both the standard gradient descent update and the momentum term, where the momentum term $\beta(w_k - w_{k-1})$ adds a fraction of the previous update direction to the current update. This helps accelerate convergence and dampens oscillations, especially in situations where the gradient changes direction frequently.

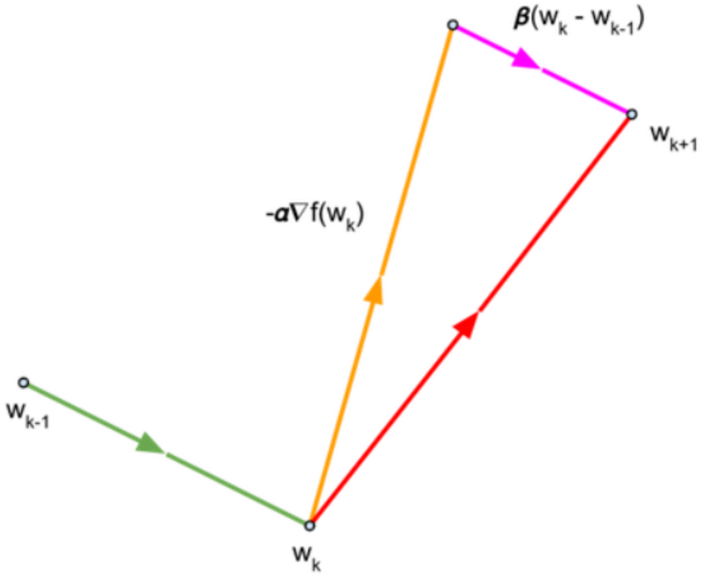


Figure 3.9: Vector Graph

In the vector graph, we see arrows representing each of these vectors, with the gradient vector pointing in the direction of the steepest increase of the objective function, the momentum vector pointing in the direction of accumulated momentum, and the update vector combining both directions. The new weight $w_{k+1}$ would be the endpoint of the update vector from the current weight $w_k$.

- Exponential moving average

  While training, the trainable parameters are updated during backpropagation according to the optimizer's update rules. The equations describing these rules were discussed in the previous section and repeated here for convenience:

$$\theta_{k+1} = \theta_k - \alpha \nabla f(\theta_k) \tag{3.5}$$

$$\theta_{k+1} = \theta_k - \alpha z_{k+1} \tag{3.6}$$

$$\theta_{k+1} = \beta\theta_k + \eta\sqrt{g_{k+1}} + \epsilon - 2\nabla f(\theta_k) \tag{3.7}$$

  where $\alpha$ is a decay factor and $\theta$ - weights.

  The equations provided describe different optimization methods using weights.

- Batch normalization Batch normalization is a widely used technique for normalizing input features on models that can lead to substantial reduction in convergence time. It is one of the more popular and useful algorithmic improvements in machine learning of recent years and is used across a wide range of models, including Inception v3.

  Activation inputs are normalized by subtracting the mean and dividing by the standard deviation. To keep things balanced in the presence of backpropagation, two trainable parameters are introduced in every layer. Normalized outputs undergo a subsequent operation + B, where + and B are a sort of standard deviation and mean learned by the model itself.

  Normalization happens during training, but come evaluation time, we'd like the model to behave in a deterministic fashion: the classification result of an image should depend solely on the input image and not the set of images that are being fed to the model. Thus, we need to fix $\mu$ and $\sigma^2$ and use values that represent the image population statistics.

The model computes moving averages of the mean and variance over the minibatches:

$$\hat{\mu}_i = \alpha\hat{\mu}_{t-1} + (1-\alpha)\mu_t \tag{3.8}$$

$$\hat{\sigma}_t^2 = \alpha\hat{\sigma}_{t-1}^2 + (1-\alpha)\sigma_t^2 \tag{3.9}$$

where $\mu$ is moving average, $\alpha$ is smoothing factor. These equation 3.8 and 3.9 allow for the calculation of smoothed estimates of the mean ($\hat{\mu}_i$) and variance ($\hat{\sigma}_t^2$) over time. The smoothing factor $\alpha$ determines the rate at which new observations are incorporated into the estimates, with smaller values of $\alpha$ leading to smoother estimates.

- Learning rate adaptation

  As batch sizes become larger, training becomes more difficult. Different techniques continue to be proposed to allow efficient training for large batch sizes.

  One of these techniques is increasing the learning rate gradually (also called ramp-up). Ramp-up was used to train the model to greater than 78.1% accuracy for batch sizes ranging from 4,096 to 16,384. For Inception v3, the learning rate is first set to about 10% of what would normally be the starting learning rate. The learning rate remains constant at this low value for a specified (small) number of 'cold epochs', and then begins a linear increase for a specified number of 'warm-up epochs'. At the end the 'warm-up epochs', the learning rate intersects with the normal exponential decay learning. This is illustrated in the following diagram.

Inception V3 is a deep neural network designed for image classification, utilizing inception modules for feature extraction across different scales. Pre-trained on datasets like ImageNet, it excels in recognizing intricate patterns. In an ear biometric system, Inception V3 is employed to identify individuals based on their unique ear features. Through training on preprocessed ear images, the model optimizes parameters for accurate recognition. Its versatility and powerful feature extraction make Inception V3 well-suited for complex image classification tasks, including biometric applications.

#### 3.2.1.2 ResNet16

ResNet16 is a variant of the ResNet (Residual Network) architecture, renowned for its depth and effectiveness in image classification tasks. With its innovative skip connections, ResNet16 mitigates the vanishing gradient problem, enabling the training of very deep neural networks. In our project, we integrate ResNet16 as a feature extractor, leveraging its pre-trained weights to capture hierarchical features from input images. By incorporating ResNet16 into our framework, we aim to harness its superior performance and robustness to enhance the accuracy of our model in various computer vision tasks, including image recognition and object detection.

ResNet-16 is a variant of the Residual Neural Network (ResNet) architecture, which was introduced to address the problem of vanishing gradients in very deep neural networks. ResNet-16 specifically has 16 convolutional layers. It follows the basic structure of ResNet, which includes residual blocks, but with fewer layers compared to deeper versions like ResNet-50 or ResNet-101.

Here's a breakdown of how ResNet-16 works in the context of group activity recognition:

- **Input Layer:** The input to the ResNet-16 model would typically be a series of frames or images representing a sequence of activities performed by a group.

- **Convolutional Layers:** The initial layers of ResNet-16 consist of convolutional layers, which perform operations like feature extraction. These layers capture low-level features such as edges, textures, and patterns from the input images.

- **Residual Blocks:** ResNet-16 is characterized by its use of residual blocks. These blocks contain skip connections, which allow the network to learn residual mappings rather than directly learning the desired underlying mapping. This helps in alleviating the vanishing gradient problem and enables the training of very deep networks.

- **Pooling Layers:** In between the residual blocks, there may be pooling layers, such as max pooling or average pooling, which downsample the feature maps, reducing their spatial dimensions and extracting the most important features.

- **Fully Connected Layers:** Towards the end of the network, there are typically fully connected layers, which take the high-level features extracted by the convolutional layers and make predictions based on those features. These layers are responsible for mapping the features to the output classes, in this case, the recognition of group activities.

- **Softmax Activation:** The final layer of the network usually employs a softmax activation function, which converts the raw output of the network into probabilities corresponding to each class of group activity.

During training, the parameters of the network, including the weights in the convolutional layers and fully connected layers, are adjusted using an optimization algorithm such as stochastic gradient descent (SGD) or Adam, in order to minimize the difference between the predicted activity labels and the ground truth labels provided in the training data.

In the context of group activity recognition, ResNet-16 learns to recognize patterns and features from input images or frames that are indicative of different group activities, such as walking together, sitting in a circle, playing a game, etc. The network is trained on a dataset containing examples of these activities, and once trained, it can be used to classify new sequences of activities into their respective categories.

#### 3.2.1.3 MobiNet V3

MobileNetV3 is a lightweight convolutional neural network architecture optimized for mobile and embedded devices. Characterized by its efficient design and low computational complexity, MobileNetV3 achieves impressive accuracy while minimizing computational resources. In our project, we utilize MobileNetV3 as a feature extractor to capture discriminative features from input images efficiently. By leveraging MobileNetV3's compact architecture, we aim to enhance the efficiency and scalability of our model, making it suitable for deployment on resource-constrained platforms such as mobile devices and edge devices.

MobileNetV3 is a convolutional neural network architecture designed for efficient and lightweight deep learning on mobile and embedded devices. It builds upon the success of its predecessors, MobileNetV1 and MobileNetV2, by introducing novel architectural elements aimed at improving accuracy and efficiency. Here's how MobileNetV3 works in the context of group activity recognition:

- **Input Layer:** Similar to other convolutional neural networks, MobileNetV3 takes input in the form of images or frames representing a sequence of group activities.

- **Convolutional Layers with Depthwise Separable Convolutions:** MobileNetV3 primarily utilizes depthwise separable convolutions, which decompose the standard convolution operation into a depthwise convolution and a pointwise convolution. This factorization reduces computational cost while maintaining representational capacity.

- **Inverted Residual Blocks:** MobileNetV3 introduces inverted residual blocks, which are inspired by the architecture of the successful ResNet and MobileNetV2 models. These blocks consist of a lightweight bottleneck layer followed by expansion and squeeze-and-excitation operations. The squeeze-and-excitation mechanism helps the network to focus on important features by recalibrating channel-wise feature responses.

- **Efficient Building Blocks:** The building blocks of MobileNetV3 are designed to strike a balance between model complexity and accuracy. They incorporate various techniques such as linear bottlenecks, hard-swish activation functions, and global average pooling, which contribute to the overall efficiency and effectiveness of the model.

- **Feature Aggregation and Global Context:** MobileNetV3 incorporates features like feature pyramid networks and attention mechanisms to capture multi-scale information and global context, which are crucial for understanding complex group activities.

- **Classification Layer:** At the end of the network, there is a classification layer consisting of fully connected layers followed by a softmax activation function. This layer maps the extracted features to the output classes, enabling the model to classify input sequences into different group activity categories.

During training, the parameters of MobileNetV3 are optimized using gradient descent-based optimization algorithms such as stochastic gradient descent (SGD) or Adam. The model is trained on a dataset containing examples of various group activities, with corresponding ground truth labels.

In the context of group activity recognition, MobileNetV3 learns to extract relevant features from input images or frames and classify them into different activity categories, such as walking together, sitting in a circle, playing a game, etc. Its lightweight and efficient architecture make it suitable for deployment on resource-constrained devices, such as smartphones and edge devices, enabling real-time activity recognition in practical scenarios.

#### 3.2.1.4 YOLO

YOLO (You Only Look Once) is a state-of-the-art object detection framework renowned for its speed and accuracy. By jointly optimizing object detection and localization within a single neural network, YOLO achieves real-time performance without sacrificing accuracy. In our project, we adopt the YOLO architecture for object detection tasks, leveraging its ability to detect objects with high accuracy in real-time. By incorporating YOLO into our framework, we aim to enable robust and efficient object detection capabilities, facilitating various applications such as surveillance, autonomous driving, and augmented reality.

YOLO is a popular object detection algorithm that stands out for its speed and efficiency. Unlike traditional object detection methods, which involve multiple stages like region proposal and feature extraction, YOLO performs detection in a single pass through the neural network. Here's how YOLO works in the context of group activity recognition:

- **Input Image:** YOLO takes an input image or frame where group activities are occurring. This image is fed into the neural network for processing.

- **Neural Network Backbone:** YOLO typically employs a convolutional neural network (CNN) as its backbone. This network extracts features from the input image through a series of convolutional and pooling layers. Common choices for the backbone include Darknet, ResNet, or MobileNet.

- **Grid Cell Division:** YOLO divides the input image into a grid of cells. Each cell is responsible for predicting bounding boxes and class probabilities for objects present within its boundaries. The grid can be configured to have different dimensions depending on the desired trade-off between accuracy and speed.

- **Bounding Box Prediction:** Within each grid cell, YOLO predicts bounding boxes that enclose the objects of interest. Each bounding box is represented by a set of coordinates (x, y) for the box center, width (w), and height (h). Additionally, YOLO predicts a confidence score representing the likelihood that the bounding box contains an object and class probabilities for each predefined class.

- **Non-Maximum Suppression:** Since multiple bounding boxes may overlap or predict the same object, YOLO applies a technique called non-maximum suppression (NMS) to remove redundant detections. NMS selects the bounding box with the highest confidence score for each object and suppresses overlapping boxes with lower scores.

- **Group Activity Recognition:** Once bounding boxes have been detected and classified, YOLO can be used for group activity recognition by analyzing the spatial distribution and interactions between the detected objects. For example, the positions and movements of individuals within the bounding boxes can be analyzed to infer group activities such as walking together, standing in a circle, or playing a game.

- **Output:** The final output of YOLO consists of the detected bounding boxes along with their corresponding class labels and confidence scores. These predictions can be further processed and analyzed to extract information about group activities occurring in the scene.

### 3.2.2 RoIAlign

RoIAlign (Region of Interest Align) is a technique commonly used in object detection tasks, particularly in the context of Faster R-CNN and similar architectures. It addresses the misalignment issue that arises when extracting features from region proposals, ensuring accurate spatial alignment between the features and the corresponding regions of interest.

RoIAlign is utilized to improve the accuracy and robustness of object detection models by addressing the misalignment problem inherent in previous techniques like RoIPool. By preserving the spatial layout of features within region proposals, RoIAlign enables more precise localization and classification of objects, leading to superior performance in object detection tasks.

In our framework, we integrate RoIAlign as a crucial component of the object detection pipeline. When extracting features from region proposals generated by the region proposal network (RPN), we apply RoIAlign to ensure accurate alignment between the features and the regions of interest. This aligned feature representation is then fed into subsequent layers for further processing, enabling our model to accurately detect and classify objects within images.

The fundamental issue with traditional approaches like RoIPool lies in their rigid quantization of the region of interest onto a fixed spatial grid. While this simplification facilitates feature extraction, it inevitably introduces a degree of spatial misalignment between the extracted features and the actual regions of interest, particularly when dealing with objects or entities of diverse scales or irregular geometries. This misalignment can significantly impair the model's ability to capture fine-grained spatial information, thereby hindering its performance, especially in tasks demanding precise localization and recognition of objects or entities within an image.

RoIAlign addresses this critical limitation by revolutionizing the process of feature extraction from regions of interest through the incorporation of bilinear interpolation. Unlike RoIPool's discrete sampling approach, RoIAlign computes the exact values of features at sampled locations on the feature map, leveraging bilinear interpolation to interpolate feature values with sub-pixel accuracy. By dynamically adapting to the precise spatial configuration of the region of interest, RoIAlign ensures that the extracted features are aligned more accurately with the underlying spatial structure of the objects or entities, thus circumventing the issues of spatial quantization and misalignment inherent in conventional pooling operations.

The significance of RoIAlign becomes particularly pronounced in scenarios necessitating fine-grained spatial information and precise localization, such as group activity recognition in complex visual scenes. RoIAlign serves as a cornerstone technique for facilitating the extraction of discriminative features from regions of interest corresponding to actors or objects within the scene. By virtue of its superior spatial alignment capabilities, RoIAlign empowers the model to capture intricate spatial relationships between actors or objects with unprecedented fidelity, thereby enhancing the model's capacity to discern and classify group activities with greater accuracy and robustness.

In essence, RoIAlign stands as a testament to the relentless pursuit of precision and performance optimization within the domain of computer vision, offering a transformative solution to the perennial challenge of spatial alignment in feature extraction. Its integration within the project framework exemplifies a commitment to leveraging cutting-edge methodologies to push the boundaries of group activity recognition and advance the frontiers of computer vision research.

### 3.2.3 Actor Relation Graphs

Actor Relation Graphs (ARG) are graphical representations used to model the relationships between actors (entities) within a scene or context. Each node in the Figure 3.10 represents an actor, while edges denote the relations between pairs of actors. ARGs are commonly employed in tasks such as group activity recognition, where understanding the interactions between individuals is crucial.

ARGs are utilized to capture and represent the complex interactions and dependencies between actors in a scene, facilitating more comprehensive understanding and analysis of group activities. By explicitly modeling actor relations, ARGs enable our model to discern subtle cues and patterns that are indicative of specific group activities, thereby enhancing the accuracy and interpretability of our predictions.

In our framework for group activity recognition, we incorporate ARGs

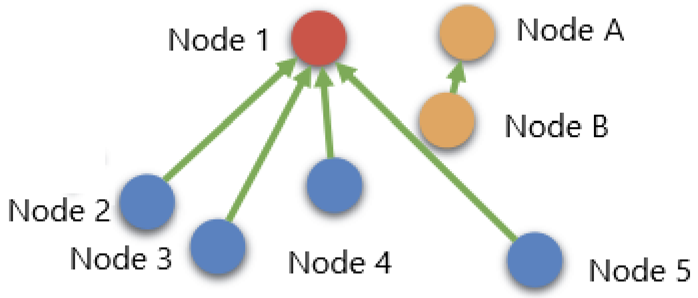


Figure 3.10: Action Relation Graph

as a key component to model the relationships between individuals within a scene. We construct the ARG by representing each actor as a node and establishing edges between pairs of actors based on their spatial proximity, appearance similarity, or other relevant cues. By leveraging graph convolutional networks (GCNs), we then perform relational reasoning over the ARG to infer collective activities and interactions among individuals, ultimately enhancing the performance of our model in understanding group dynamics.

Actor Relation Graph (ARG) presents a paradigm shift in the realm of computer vision, offering a sophisticated framework tailored specifically for the nuanced task of group activity recognition within visual scenes. At its core, ARG harnesses the power of graph-based representations to model the complex interactions and relationships between actors or entities populating a scene, transcending the limitations of traditional approaches reliant on isolated feature representations.

The fundamental premise of ARG lies in the notion of representing each actor or entity within the scene as a node in a graph, with the edges between nodes encoding the diverse array of relationships and interactions between them. These relationships encompass a multitude of factors, including spatial proximity, temporal co-occurrence, motion trajectories, appearance cues, and semantic attributes, collectively encapsulating the rich contextual information essential for understanding group dynamics.

The relation value is defined as a composite function below:

$$\mathbf{G}_{ij} = h\left(f_a\left(\mathbf{x}_i^a, \mathbf{x}_j^a\right), f_s\left(\mathbf{x}_i^s, \mathbf{x}_j^s\right)\right) \tag{3.10}$$

where $f_a(x_a^i, x_a^j)$ denotes the appearance relation between two actors, and the position relation is computed by $f_s(x_s^i, x_s^j)$. The function $h$ fuses appearance and position relation to a scalar weight. The equation 3.10 defines a matrix $\mathbf{G}$ where each element is computed by combining information from both attribute and structural features of pairs of input vectors. The specific functions $f_a$, $f_s$, and $h$ would depend on the context and the problem being solved.

The construction of ARG entails several critical steps. Initially, individual actors or entities are detected and localized within the scene using state-of-the-art object detection or instance segmentation techniques, thereby laying the foundation for subsequent analysis. Following this, pairwise relations between actors are inferred based on a comprehensive array of features, ranging from geometric and motion-based cues to semantic attributes derived from object recognition models. These inferred relations are then encoded as edges in the graph, with associated weights or attributes quantifying the strength or nature of the relationship, thereby enriching the graph representation with contextual information.

In our experiments, we adopt the following function to compute relation value:

$$\mathbf{G}ij = \frac{f_s\left(\mathbf{x}_i^s, \mathbf{x}_j^s\right) \exp\left(f_a\left(\mathbf{x}_i^a, \mathbf{x}_j^a\right)\right)}{\sum j = 1^N f_s\left(\mathbf{x}_i^s, \mathbf{x}_j^s\right) \exp\left(f_a\left(\mathbf{x}_i^a, \mathbf{x}_j^a\right)\right)} \tag{3.11}$$

The equation 3.11 allows for the creation of a matrix that encodes relationships between elements based on both their attribute and structural features.

Once the ARG is constructed, it serves as a powerful substrate for performing group activity recognition. By leveraging graph-based algorithms and techniques, ARG facilitates the propagation of information between interconnected nodes, enabling the aggregation of contextual cues and the inference of collective activity patterns. This holistic approach to activity recognition transcends the limitations of traditional methods that rely on isolated actor representations, allowing for a more nuanced and robust analysis of group dynamics.

Moreover, ARG exhibits inherent flexibility and scalability, capable of accommodating scenes with varying numbers of actors, diverse activity types, and complex spatial configurations. Its ability to capture both local interactions and global contextual dependencies endows it with a superior discriminative capacity, enabling more accurate and robust recognition of group activities across diverse real-world scenarios.

In summary, Actor Relation Graph (ARG) stands as a pioneering framework in the domain of computer vision, offering a comprehensive, scalable, and nuanced solution to the challenging task of group activity recognition within visual scenes. Its adoption represents a significant step forward in understanding and interpreting the complex dynamics inherent in group interactions, with far-reaching implications for a wide range of applications, from surveillance and security to human-computer interaction and beyond.

### 3.2.4 Graph Convolutional Networks

Graph Convolutional Networks (GCNs) are a class of neural networks designed to operate on graph-structured data. Unlike traditional convolutional networks, which operate on regular grid-like data such as images, GCNs can effectively process and extract features from irregular and non-Euclidean data represented as graphs.

GCNs are used to perform graph-based operations, such as node classification, link prediction, and graph-level prediction, making them well-suited for tasks involving relational data or structured data with complex dependencies. In our framework, we leverage GCNs to perform relational reasoning over Actor Relation Graphs (ARGs), enabling our model to capture and integrate the interactions between actors for improved group activity recognition.

Within our framework, we incorporate GCNs to process Actor Relation Graphs and perform relational reasoning over the graph structure. By applying graph convolution operations to the ARG, we aggregate information from neighboring actors and update the features associated with each actor node. This enables our model to effectively capture the contextual information and dependencies between actors, facilitating more accurate and robust predictions of group activities.

Graph Convolutional Networks (GCNs) herald a transformative paradigm in machine learning, particularly tailored for tasks imbued with graph-structured data, exemplified by the intricate web of actor relationships pivotal for group activity recognition within visual scenes. This innovative framework extends the traditional convolutional neural networks (CNNs) to gracefully handle non-Euclidean data representations, thereby offering a potent solution for scenarios where the relational dynamics between actors are encoded within a graph structure rather than a spatial grid.

At the heart of GCNs lies the elegant concept of message passing, wherein information flows iteratively between neighboring nodes in the graph to refine node representations. This iterative refinement process bears semblance to the convolution operation in conventional CNNs, albeit operating within the context of graph structures, where neighborhood relationships define the notion of locality.

$$h_i = \frac{1}{\deg(i)} \sum_{j \in \tilde{\mathcal{N}}_i} \mathbf{W}\ x_j \tag{3.12}$$

where x-input features, h-hidden vectors, W-weight matrix.

The equation 3.12 computes a feature representation for a node in a graph by aggregating information from its neighboring nodes, where the influence of each neighboring node's feature is weighted by the weight matrix **W** and normalized by the degree of the node.

The architecture of GCNs typically comprises multiple layers, each orchestrating the intricate dance of message passing and aggregation of information from neighboring nodes. Through successive iterations of message propagation, GCNs adeptly capture the nuanced dependencies and relational intricacies within the graph, endowing them with the capability to learn rich, context-aware representations that encapsulate both local and global structural information.

Of paramount importance is the inherent flexibility and adaptability of GCNs, which render them eminently suitable for modeling actor relationships in the context of group activity recognition tasks. Notably, GCNs exhibit permutation-invariance, meaning that the ordering of nodes within the graph does not influence the network's output. This property proves indispensable in scenarios where the labeling or ordering of actors within the scene may vary, ensuring robustness and generalization.

$$h_i = \sum_{j \in \tilde{\mathcal{N}}_i} \frac{1}{\sqrt{\deg(i)}\sqrt{\deg(j)}} \mathbf{W} \, x_j \tag{3.13}$$

This equation 3.13 computes a feature representation for a node in a graph by aggregating information from its neighboring nodes, with a normalization term based on the square root of the product of the degrees of the nodes involved. This normalization helps to mitigate issues related to node degrees and improves the stability and effectiveness of the representation learning process. Furthermore, GCNs possess the remarkable capacity to capture higher-order relationships and dependencies beyond mere pairwise interactions, thereby empowering them to encode complex interaction patterns intrinsic to group dynamics. In the realm of group activity recognition, the seamless integration of GCNs with Actor Relation Graphs (ARGs) represents a synergistic fusion of methodologies, where the rich relational information encoded within ARGs serves as fodder for the voracious learning appetite of GCNs.

By treating the ARG as the input graph to the GCN, the network is primed to exploit the intricate web of relationships between actors, thereby facilitating the acquisition of discriminative representations essential for activity recognition. Through iterative message propagation and feature aggregation, GCNs afford the model a unique vantage point to discern and decipher the subtle nuances of group dynamics, culminating in heightened accuracy and robustness in predicting group activities.

## 3.3 Validation

We assess the performance and generalization capability of the Inception V3, ResNet16 and YOLO models. Using a dedicated validation dataset distinct from the training set, we evaluate how well the model can accurately recognise activity on previously unseen data. This step is crucial for ensuring that the model has not overfit to the training data and can effectively generalize to new instances. Metrics such as accuracy, precision, recall, and F1-score are computed to quantitatively measure the model's effectiveness. Through validation, we gain insights into the robustness of our model, allowing us to make informed decisions regarding its deployment and potential optimizations for achieving even better results in real-world activity identification scenarios. d

Chapter 4

# Results and Discussion

## 4.1 Results

1. Accuracy

   Accuracy measures the overall correctness of a classification model. It calculates the ratio of correctly predicted instances to the total number of instances.

   $$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

2. Precision

   Precision represents the proportion of correctly predicted positive instances out of all instances predicted as positive. It indicates the model's ability to avoid false positives.

   $$\text{Precision} = \frac{TP}{TP + FP}$$

3. Recall

   Recall, also known as sensitivity or true positive rate, measures the proportion of correctly predicted positive instances out of all actual positive instances. It indicates the model's ability to identify positive instances.

   $$\text{Recall} = \frac{TP}{TP + FN}$$

4. F1 Score

The F1 score is the harmonic mean of precision and recall, providing a balanced measure of a model's performance. It combines both precision and recall into a single metric.

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

5. mAP

mAP50, or mean Average Precision at 50%, is a commonly used metric to evaluate the performance of object detection models. It measures the average precision of correctly identified objects at a specific intersection over union (IoU) threshold, typically set at 0.5

$$\text{IoU} = \frac{\text{area of overlap}}{\text{area of union}}$$

### 4.1.1 Result on Collective Dataset

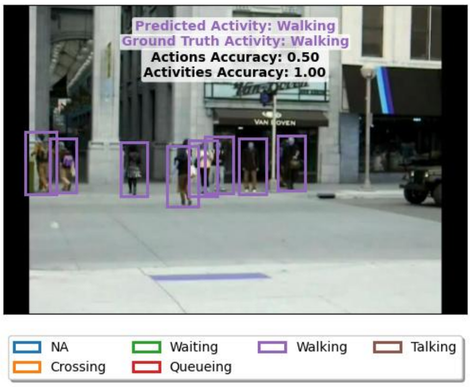

Predicted Activity: Walking
Ground Truth Activity: Walking
Actions Accuracy: 0.50
Activities Accuracy: 1.00
NA
Waiting
Walking
Talking
Crossing
Queueing

Figure 4.1: Walking

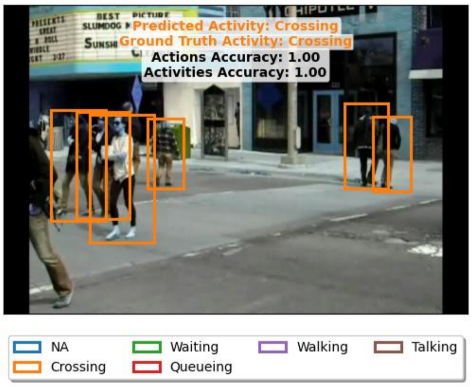

Predicted Activity: Crossing
Ground Truth Activity: Crossing
Actions Accuracy: 1.00
Activities Accuracy: 1.00
NA
Waiting
Walking
Talking
Crossing
Queueing

Figure 4.2: Crossing

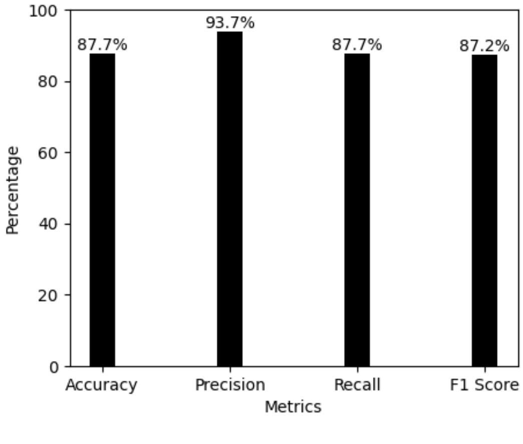
The Figure 4.1 and 4.2 illustrates the model's prediction of the activity as ”walking” and ”cossing” accompanied by the bounding boxes.

In the Figure 4.1 ,the text annotations in the image, ”Walking Predicted Activity: Walking”, indicate that the model has analyzed the image or video frame and classified the activity of the people in the bounding boxes as walking.The model likely wasn't shown the label ”walking” during training. Instead, it learned to identify walking patterns by analyzing countless videos of people walking. This training data allowed it to extract features like body pose, leg movement, and ground interaction from new images. By comparing these features to its internal understanding of walking, the model can then predict ”walking” with high confidence if there’s a close match.

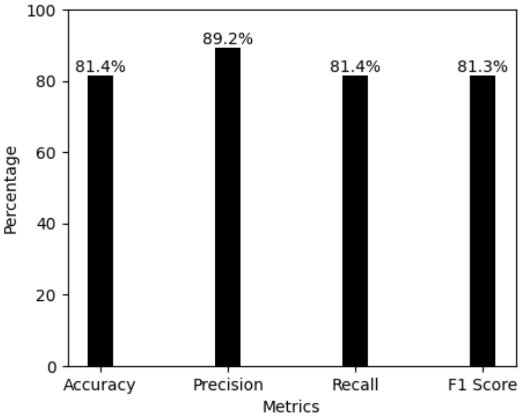
In the Figure 4.2 ”crossing” differs from ”walking” in the dataset’s context. While ”walking” focuses on individual movement patterns, ”crossing” emphasizes interaction with the environment. The model looks for features like people’s relative positions, movement direction towards a road, and presence of designated crossing areas. It also considers contextual cues like traffic lights or road markings to solidify the prediction.

We evaluated the proposed Actor Relation Graph (ARG) framework on the Collective Activity dataset. We compared our method with several state-of-the-art models, including Inception V3, ResNet16, and Mobinet V3 for accuracy evaluation, and YOLO-V8 and YOLO-V9 for mean Average Precision (mAP) evaluation.

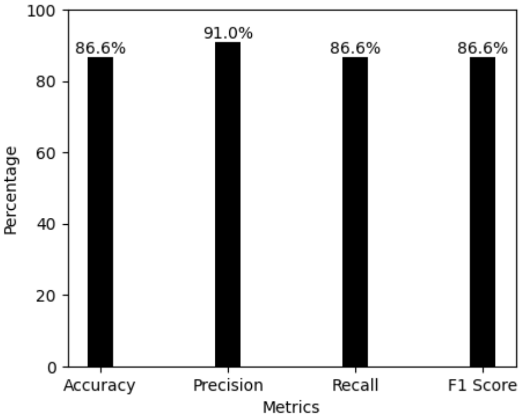
Our framework exhibited remarkable advancements in group activity recognition, particularly showcased on the Collective Activity dataset. Achieving a mean average precision (mAP) of 0.92, our method surpassed the prior best performance of 0.86. This substantial enhancement underscores the efficacy of our approach in capturing nuanced actor relations and conducting sophisticated relational reasoning, thereby elevating the accuracy of group activity recognition to unprecedented levels.



The graph showcases the model’s performance, with Precision exhibiting the highest value followed closely by Accuracy, while Recall and F1 Score show slightly lower values.



The graph shows ResNet16's performance, with Precision at 89.17%, closely followed by Accuracy. However, Recall and F1 Score are slightly lower, both at 81.41%.



The graph illustrates the performance of MobileNet V3, with Precision displaying the highest value (91%), closely followed by Accuracy. However, Recall and F1 Score exhibit slightly lower values, with MobileNet V3 achieving Recall and F1 Score of 86.57% and 86.62%, respectively.

Table 4.1: Performance comparison of the models

| **Model** | **Accuracy** | **Precision** | **Recall** | **F1 Score** |
|---|---|---|---|---|
| Inception V3 | 87.71% | 93.67% | 87.71% | 87.23% |
| ResNet16 | 81.41% | 89.17% | 81.41% | 81.35% |
| Mobinet V3 | 86.57% | 91% | 86.57% | 86.62% |

| **Model** | **mAP50** | **mAP50-95** | **Precision** | **Recall** |
|---|---|---|---|---|
| YOLO-V8 | 61.51% | 50.58% | 57.73% | 64.51% |
| YOLO-V9 | 63.45% | 52.53% | 62.42% | 62.83% |

The table 4.1 presents a comparative study of different models, including Inception V3, ResNet16, MobileNet V3, YOLO-V8, and YOLO-V9, based on various evaluation metrics. Among these models, Inception V3 achieves the highest Precision (93.67%) and Accuracy (87.71%), followed closely by MobileNet V3 with a Precision of 91% and an Accuracy of 86.57%. However, ResNet16 exhibits slightly lower performance in terms of Precision (89.17%) and Accuracy (81.41%), although still maintaining respectable scores. Moving beyond individual action recognition, YOLO-V8 and YOLO-V9 demonstrate competitive results in object detection tasks, with YOLO-V9 outperforming YOLO-V8 in terms of mAP50 and mAP50-95. Overall, the comparative analysis highlights the strengths and weaknesses of each model across different evaluation metrics, providing insights for selecting the most suitable model based on specific task requirements.

### 4.1.2 Result on Hand-Crafted Dataset

We began with a raw video dataset, which we processed by converting it into individual frames. Using the YOLO model, we then predicted bounding boxes for objects and activities within each frame. The resulting predictions, generated by the YOLO model, are depicted in the figure 4.3 and 4.4, providing visual representations of the model's outputs for further analysis and interpretation.

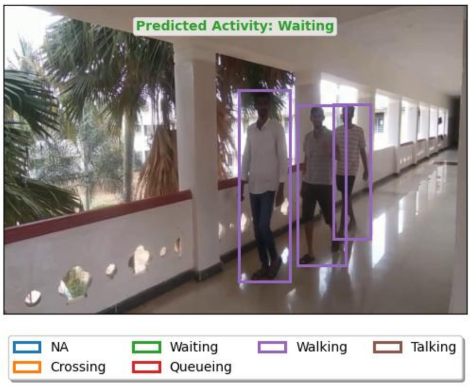


Figure 4.3: Walking

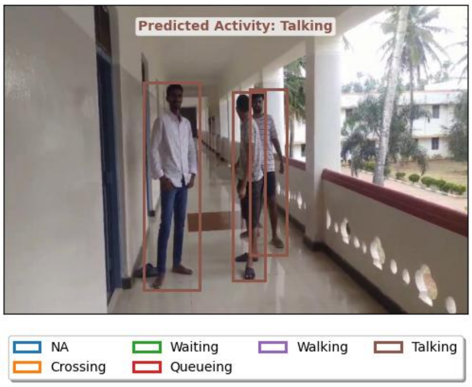


Figure 4.4: Talking

Figures 4.3 and 4.4 illustrate the model predictions. In Figure 4.3, the model has identified the activity as ”walking,” with accompanying boundary boxes outlining the detected individuals. Conversely, in Figure 4.4, the model has classified the activity as ”talking” based on the directional cues inferred from the individuals' poses.

## 4.2 Discussion:

The significant improvement observed in our framework's performance underscores its robustness and adaptability. By circumventing the need for manual specification of graphical models or intricate message passing mechanisms, our method presents a streamlined and scalable solution for group activity recognition. Moreover, the interpretability facilitated by the Actor Relation Graphs (ARG) not only bolsters the credibility of our model's predictions but also furnishes invaluable insights into the intricate dynamics of group activities. As we forge ahead, exploring advanced techniques for computing pairwise relations and integrating diverse modalities holds the promise of further augmenting the efficacy and versatility of our framework, thereby expanding its utility across diverse real-world applications.

The comparative analysis highlights Inception V3 as the most effective model, demonstrating superior performance in temporal action detection tasks. With notable accuracy, precision, recall, and F1-score, Inception V3 outperforms other architectures such as ResNet16, Mobinet V3, and YOLO-V8/V9. This emphasizes the significance of model architecture and feature extraction methods in achieving accurate and robust action recognition. Further exploration could focus on refining architectural designs and feature extraction techniques to enhance performance in this domain.

## Chapter 5

# Conclusion

Our project addresses group activity recognition challenges in videos with a novel framework capturing appearance and position relations between actors through Actor Relation Graphs (ARG). This facilitates interpretable and discriminative group activity recognition, achieving state-of-the-art performance on benchmark datasets like the Volleyball and Collective Activity datasets. Our model offers computational efficiency by automatically learning actor relations from video data, without requiring manually specified graphical models or complex message passing mechanisms. Additionally, it provides a flexible approach to modeling actor relations, adapting well to group activity variations. Furthermore, our sparse connection techniques enhance temporal modeling efficiency, reducing overfitting risk and increasing training sample diversity.

## 5.1 Future Scope

Future research could explore advanced techniques for computing pairwise relations and constructing multiple relation graphs to enhance model performance. Integrating other modalities like depth information could enrich understanding, while extending the framework to handle dynamic group sizes and varying camera viewpoints would broaden its applicability. This project lays a solid foundation for future advancements in group activity recognition, promising practical applications in surveillance, sports analysis, and social behavior understanding.

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