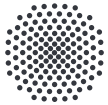

University of Stuttgart
Germany

Gaze-based Transformer for Improving Action Recognition in Egocentric Videos

Master Thesis

Mengze Lu

July 14, 2024

Perceptual User Interfaces Group, University of Stuttgart

www.perceptualui.org

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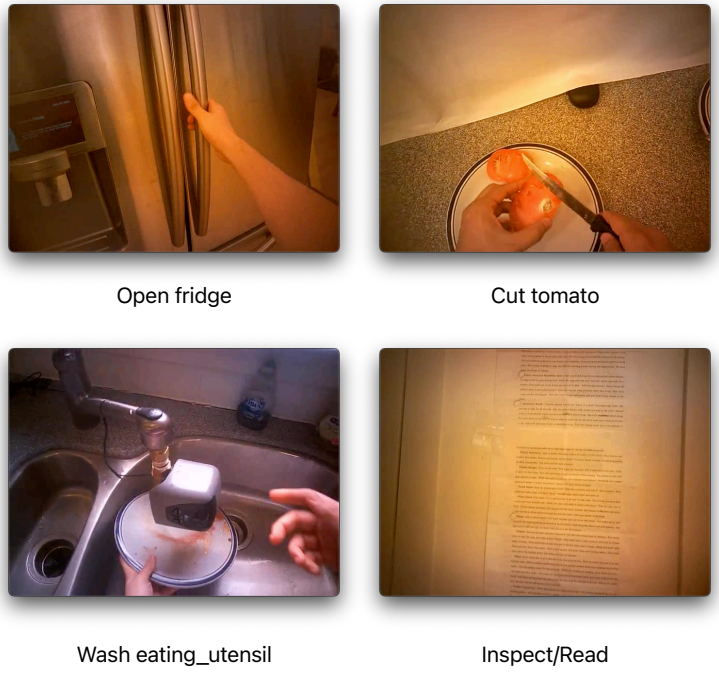
Action Recognition

Task:

- Identify and categorize human actions into predefined classes.



Source: Videos with action label

Egocentric Video

Source: Li et al. [2020] Eye tracking glasses used in video recording.

Key Features:

- First-person View (FPV)
- Hand and object interactions
- Large scene changes and diverse backgrounds

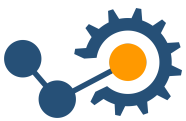
Significance of Gaze in Action Recognition

Gaze information:

- Crucial for understanding human intention
- Closely linked to object-oriented actions

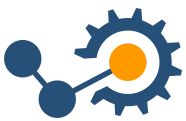
Potential of gaze information:

- Enhances the precision of action recognition



The Goal of this Thesis

Objective: Improve the accuracy of transformers for action recognition by integrating gaze data.



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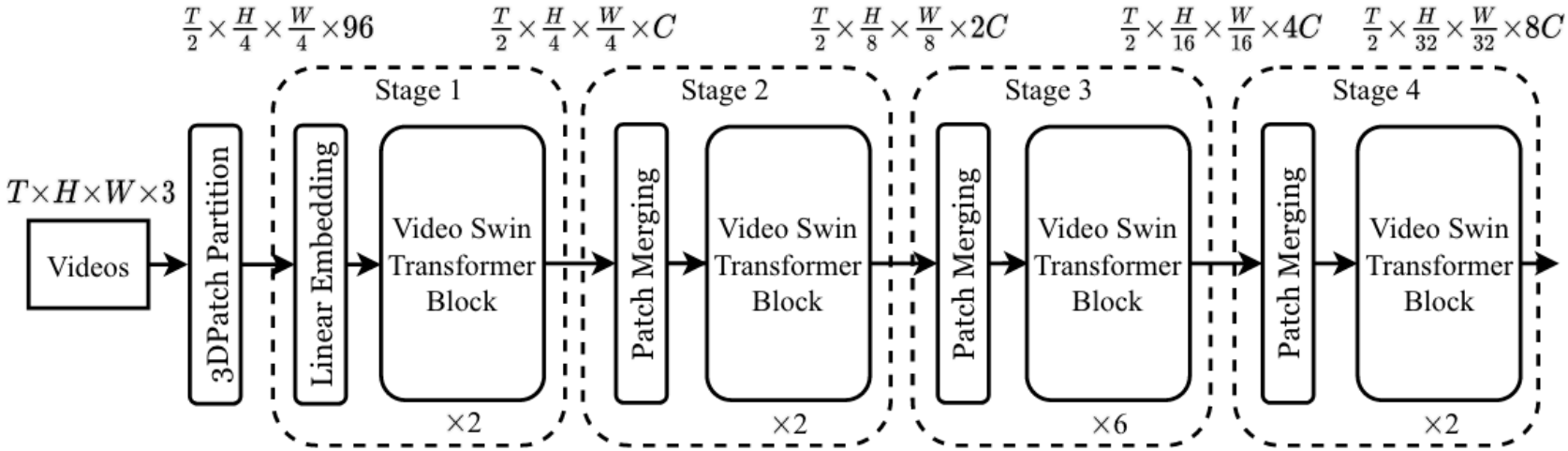
Related Works

Video Swin Transformers

Video Swin Transformer



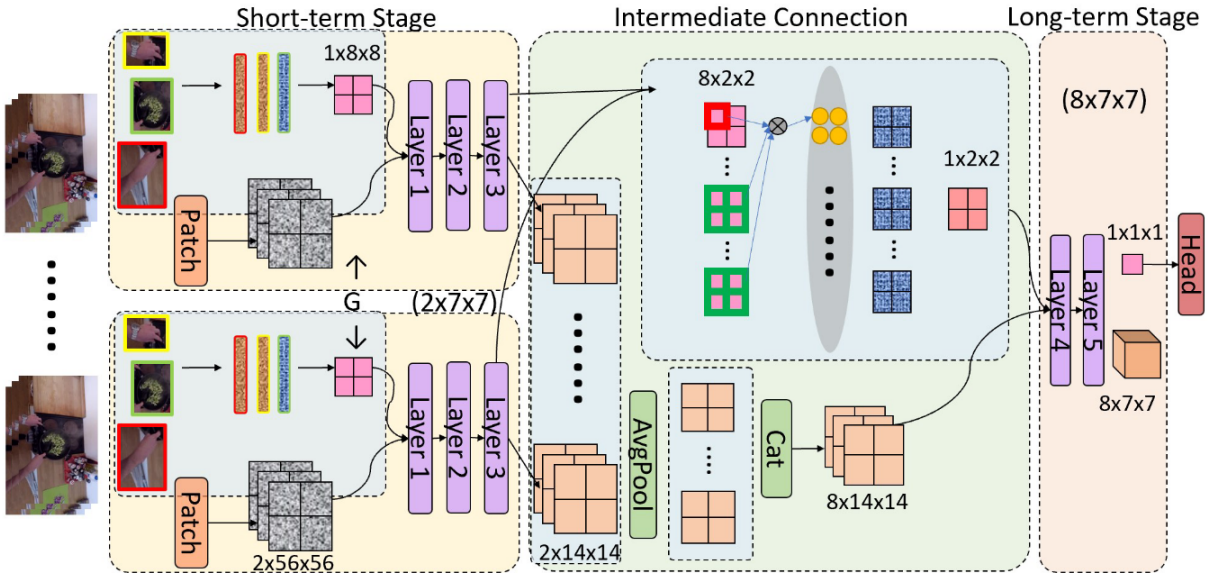
Source: Overview of the Video Swin Transformer Architecture. Liu et al. [2021]

- Processes inputs through a series of Swin Transformer blocks
- 3D Shifted Window Self-Attention
- Used as the backbone in the proposed model.

Related Works

State-of-the-Art Vision Transformer EgoViT

State-of-the-Art Vision Transformer EgoViT



Source: Pan [2023] The structure of EgoViT.

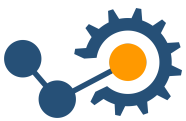
Features of the Structure:

- Designed for egocentric video
- Seamlessly integrate with different vision transformers

State-of-the-Art Vision Transformer EgoViT

Contribution of EgoViT:

- Incorporates hand-object interaction features.
- Dynamic class token (DCT): Focus on the informative parts
- Pyramid Architecture with Dynamic Merging (PADM): Effective processing large movements



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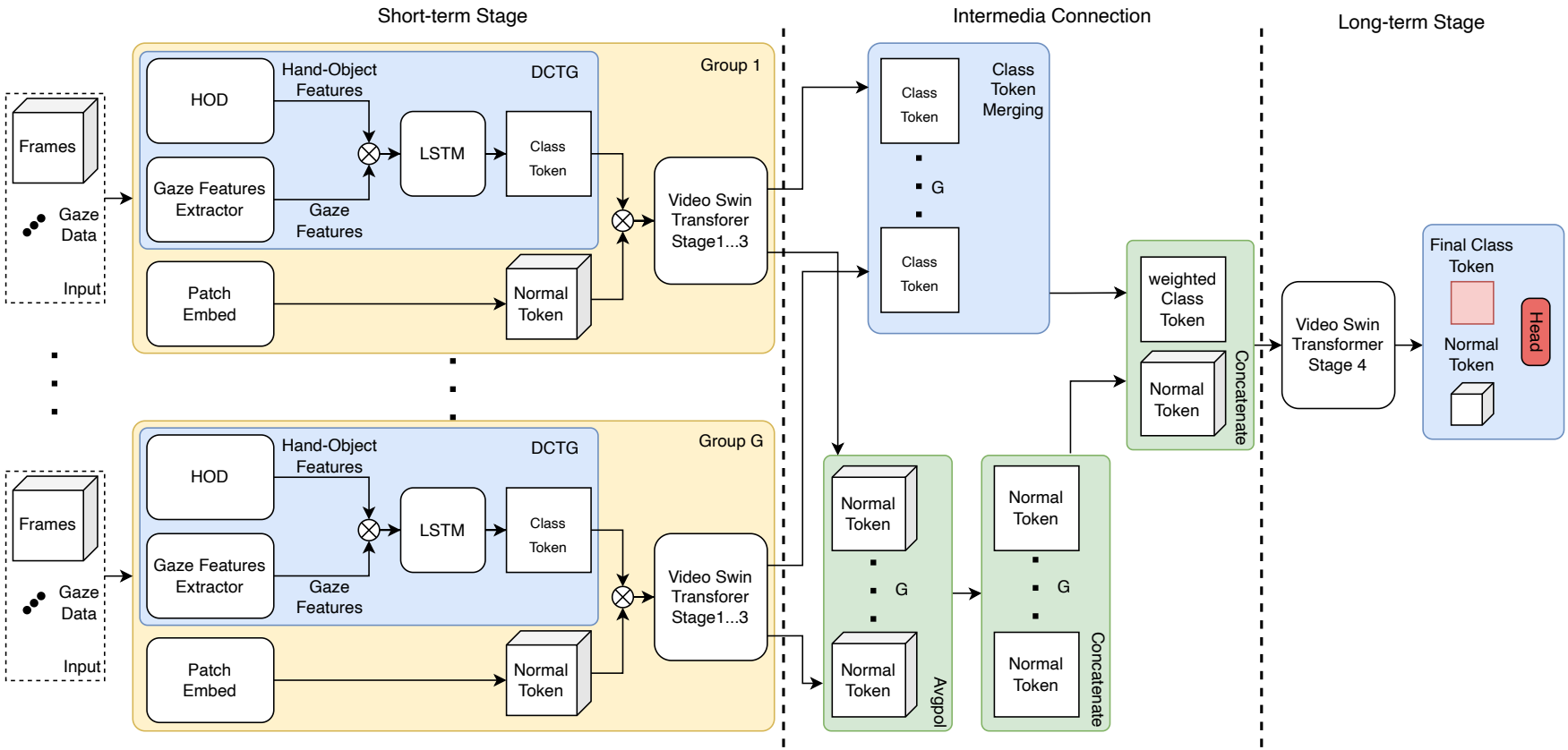
Gaze Enhanced EgoViT

The Structure of Gaze Enhanced EgoViT

The Structure of Gaze Enhanced EgoViT



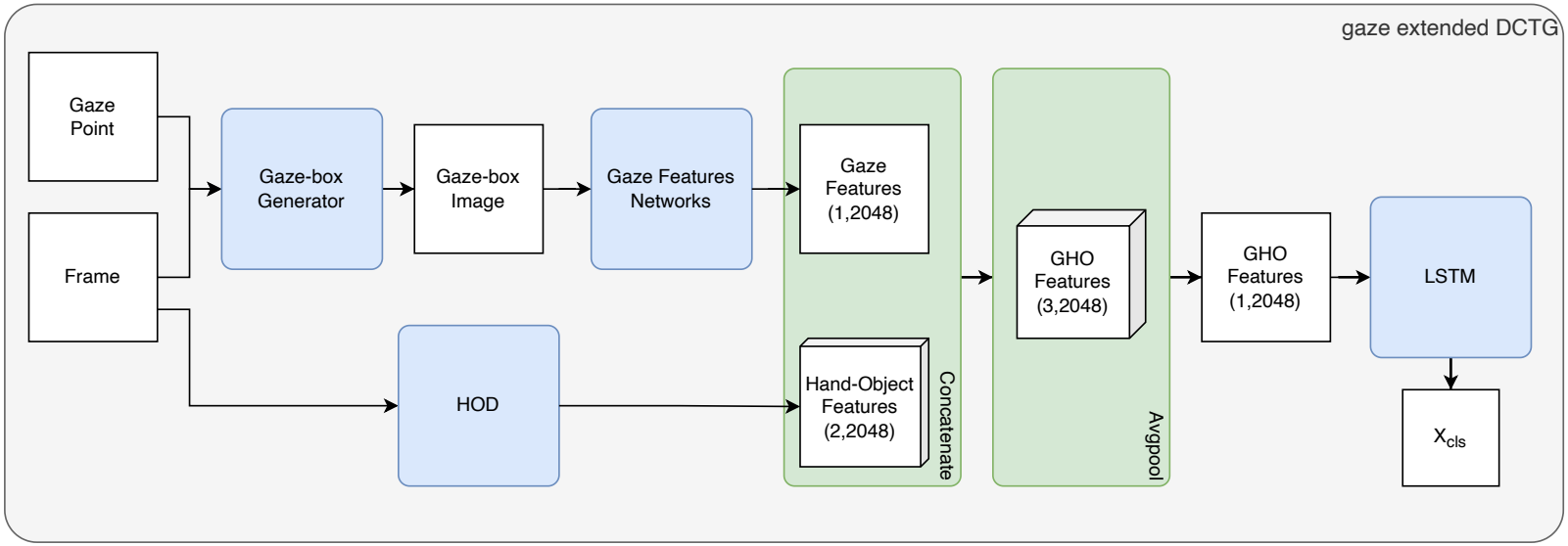
Source: The Structure of Gaze Enhanced EgoViT

- Architecture: Based on EgoViT
- DCTG extended with gaze features extract module

Gaze Enhanced EgoViT

Key Components

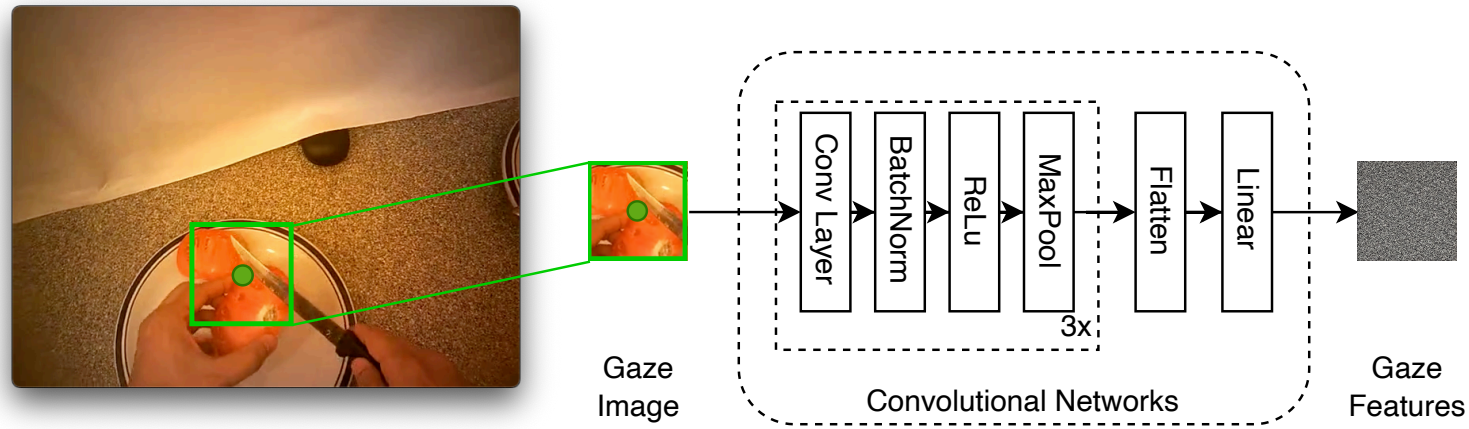
Gaze Enhanced DCTG



Source: Illustration of the Dynamic Class Token Generator with Gaze Information.

- G features and HO features are fused to form GHO features.
- Employs an LSTM to generate the class token, enhancing temporal coherence.

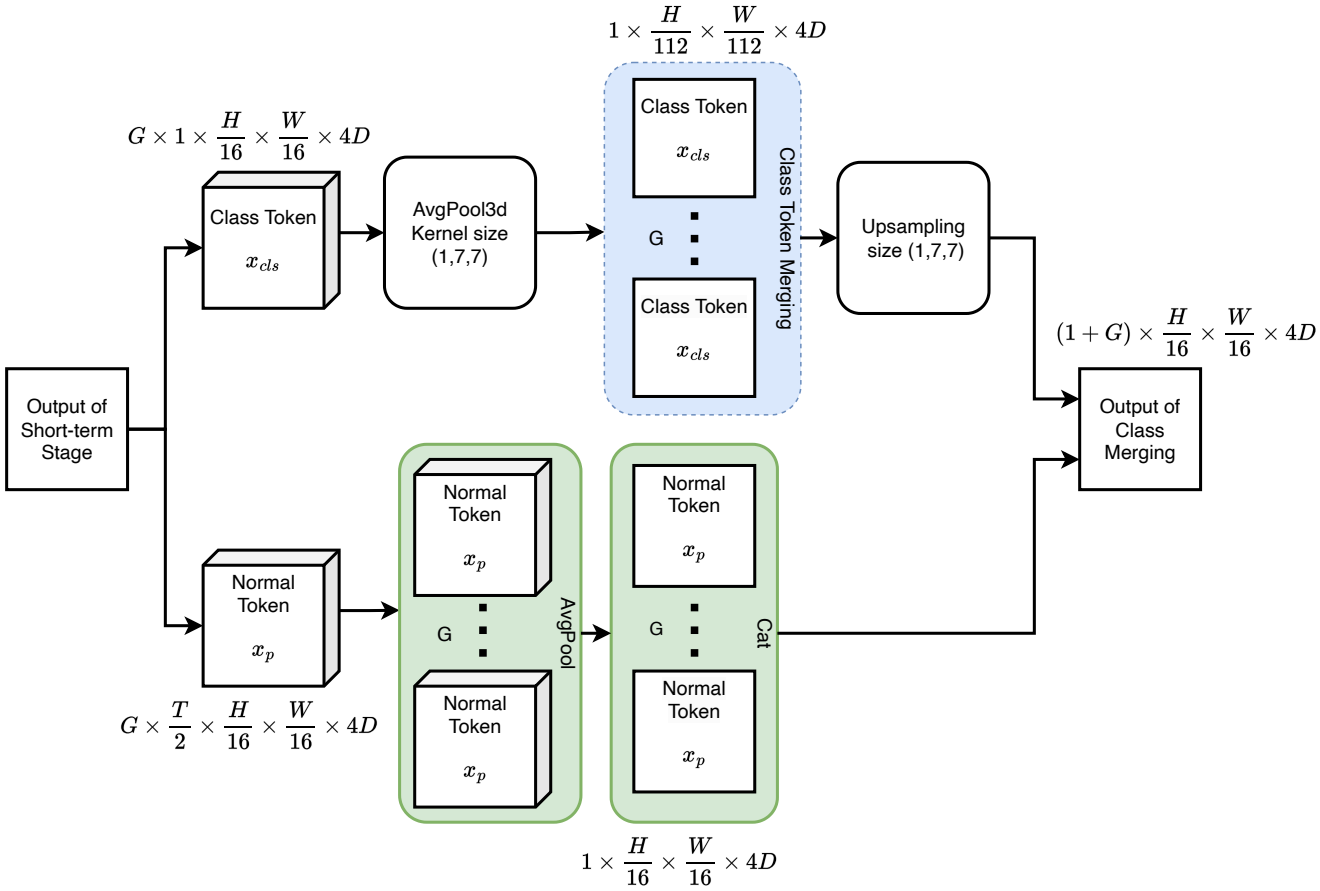
Gaze Features Extraction



Source: Illustration of the Gaze Features Extraction.

Gaze point → gaze-box image → Conv Networks → gaze features

Dynamic Merging Module



Source: Illustration of the Dynamic Merging Module.

- The class token and normal token are merged separately.
- Input $\rightarrow$ G-x_{cls}, G-x_p $\rightarrow$ Weighted x_{cls}, x_p

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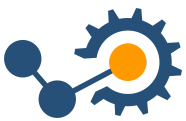


Dataset

EGTEA Gaze+:A large-scale dataset for FPV actions and gaze analysis

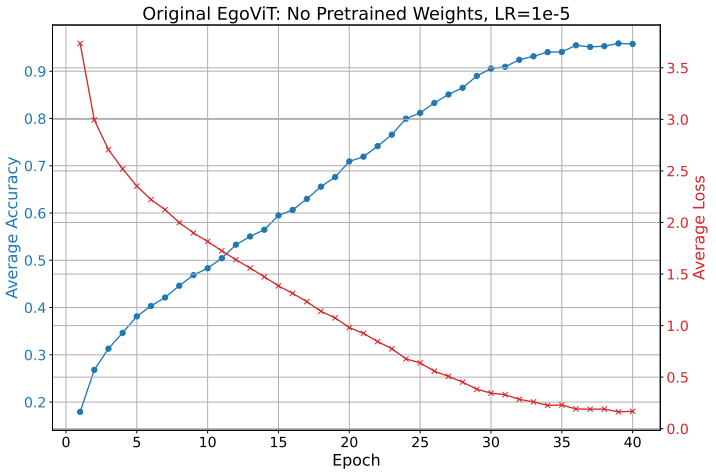
- Gaze tracking data available at 30Fps
- Frame-level action annotations

Source: Li et al. [2020] A frame from the dataset showing gaze point.

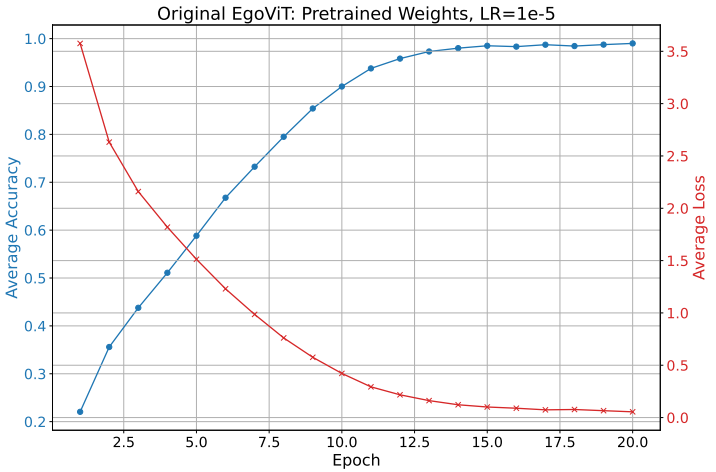
Dataset

- Gaze-Hand-Object (GHO) features are preprocessed offline.
- Each video is sampled at an average of 32 frames.
- Dataset structure:
  (Frames[32,3,224,224], GHO-Features[32,3,2048], Label[1])

Training the Original EgoViT



Source: Training accuracy and loss of the original EgoViT without pretrained weights.



Source: Training accuracy and loss of the original EgoViT with pretrained weights.

- Both models reached similar training accuracy and loss.
- The model with pretrained weights converges faster.

Test Results of original EgoViT with HO Features

Experiment ID	Top-1 Acc.(%)	Top-5 Acc.(%)	Mean Class Acc.(%)
Orig_HO_no_pretrain	51.5	78.5	38.8
Orig_HO	51.7	75.2	40.6

Discussion:

- The model with pretrained weights has higher top-1 and mean class accuracy
- Pretrained weights reduce the training time significantly

Test Results of Original EgoViT with HO Features

Experiment ID	Top-1 Acc.	Top-5 Acc.	Mean Class Acc.
Orig_HO	51.7	75.2	40.6
Enh_GHO	51.4	76.7	40.0
Enh_G	48.9	75.1	37.7

Discussion:

- Enh_GHO: slightly lower top-1 and mean class accuracy than Orig_HO.
- Enh_G: Lowest accuracy among the three models.
- The gaze features need further improvement.

Improve the quantity of the gaze data

- Gaze version 1 (GHO & G): Uses only fixation gaze tracking data.
- Gaze version 2 (GHO_v2 & G_v2): Uses both fixation and saccade gaze tracking data.
- Gaze version 2 has fewer random gaze features, enhancing the overall data quality.

Training the Gaze Enhanced EgoViT

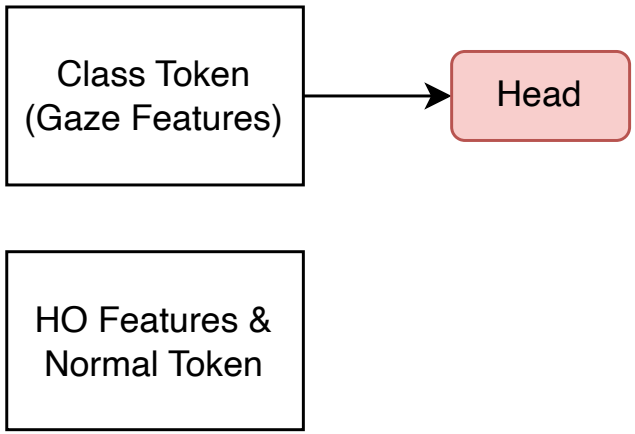
Test Results on Gaze Version 1 and Gaze Version 2

Experiment ID	Top-1 Acc.(%)	Top-5 Acc.(%)	Mean Class Acc.(%)
Enh_GHO	51.4	76.7	40.0
Enh_G	48.9	75.1	37.7
Enh_GHO_v2	52.0	76.3	38.7
Enh_G_v2	50.0	76.2	38.0

Discussion:

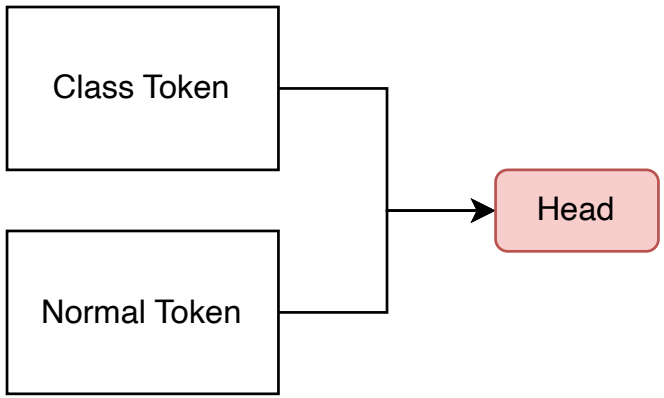
- Enh_G_v2 shows significant improvement in all three metrics.
- The quality of gaze features is important for action recognition.

Training EgoViT Variants



Source: Enhanced EgoViT Version 2

- Enh_v2_GHO_: Uses only gaze features for classification.



Source: EgoViT Version 3

- Orig_v3, Enh_v3: Use class token and normal token for classification.

Training EgoViT Variants

Test Results on EgoViT Variants

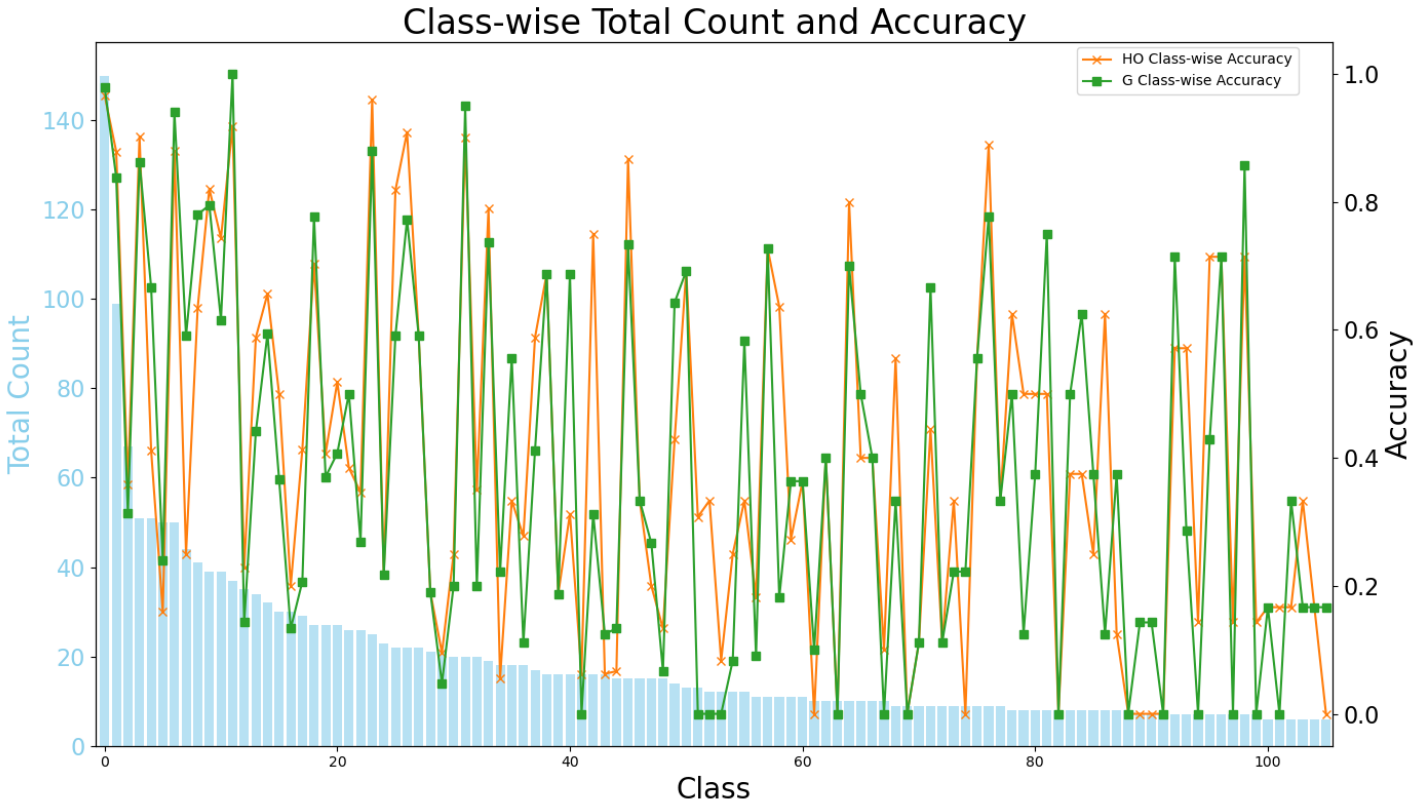
Training Method	Top-1 Acc.(%)	Top-5 Acc.(%)	Mean Class Acc.(%)
Enh_GHO_v2	52.0	76.3	38.7
Enh_v2_GHO_v2	50.4	75.8	38.3
Enh_v3_GHO_v2	51.2	77.9	39.2
Orig_HO	51.7	75.2	40.6
Orig_v3_HO	51.1	77.4	40.5
Enh_G_v2	50.0	76.2	38.0
Enh_v3_G_v2	50.8	75.9	37.8

Discussion:

- Enh_v2 shows lower performance
- Enh_v3 and Orig_v3 improve only top-5 accuracy

Possible Reason: Information in the class token and normal token is already exchanged in 3D Shifted Window Self-Attention.

Distribution of Dataset



Source: Visualization of the dataset and model predictions.

- The dataset is imbalanced, leading to overfitting on the majority class.
- The model with gaze features performs poorly in predicting movement actions.

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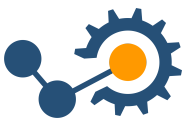
Future Works

Conclusion:

- Additional gaze features could improve the model's performance.
- The quality of the gaze features is Crucial for improving the accuracy of action recognition.

Future Works:

- Study the impact of gaze region size.
- Use a pretrained network, such as an Autoencoder, to generate gaze features.



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Y. Li, M. Liu, and J. M. Rehg. In the eye of the beholder: Gaze and actions in first person video. *arXiv:2006.00626 [cs]*, Oct 2020. URL `http://arxiv.org/abs/2006.00626`.

Z. Liu et al. Video swin transformer. *arXiv preprint arXiv:2106.13230*, 2021. URL `http://arxiv.org/abs/2106.13230`.

C. e. a. Pan. Egovit: Pyramid video transformer for egocentric action recognition. *arXiv:2303.08920 [cs]*, 2023. URL `http://arxiv.org/abs/2303.08920`.