Lightweight Vision Transformer Framework for Real-Time Human–Object Interaction Recognition

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Abstract
Human–Object Interaction (HOI) recognition is a fundamental task in intelligent computing systems, enabling machines to understand how humans engage with surrounding objects in real-time environments. Traditional deep learning approaches for HOI rely heavily on convolutional architectures, which often struggle with long-range dependencies and are computationally expensive for edge deployment. This paper proposes a Lightweight Vision Transformer Framework (LVTF) designed specifically for efficient and accurate real-time HOI recognition. The framework employs a patch-based visual encoder combined with optimized multi-head attention mechanisms to capture global contextual relationships between humans and objects. A lightweight decoder further refines these representations to generate interaction labels with minimal latency. Experimental evaluations conducted on benchmark HOI datasets demonstrate that the LVTF achieves competitive accuracy while reducing computational complexity by nearly 40% compared to conventional transformer and CNN-based models. The reduced model footprint and low inference delay make the proposed approach highly suitable for real-time intelligent applications, including smart surveillance, assistive robotics, and human–computer interaction systems.

Keywords: *Vision transformer, human–object interaction, real-time recognition, lightweight architecture, attention mechanism, intelligent systems.*

1. Introduction

Human–Object Interaction (HOI) recognition has emerged as a critical component in intelligent computing systems, enabling machines to understand not only what objects are present in a scene but also how humans interact with them. This capability plays a vital role in numerous real-world applications, including advanced surveillance systems, activity monitoring, assistive robotics, human–computer interaction interfaces, and smart environments. As the demand for real-time intelligent systems grows, the ability to accurately and efficiently interpret complex human–object dynamics has become increasingly significant.

Traditional HOI recognition models rely heavily on convolutional neural networks (CNNs) due to their strong spatial feature extraction capabilities. While CNN-based methods have achieved considerable progress, they suffer from inherent limitations. Their restricted receptive field often makes it challenging to capture global dependencies between humans and objects distributed across different regions of an image. Moreover, CNN architectures tend to be computationally heavy, making them unsuitable for real-time inference on low-power devices or edge computing platforms. As HOI recognition tasks become more complex and datasets grow larger, these limitations become more pronounced, necessitating a shift toward more flexible and efficient architectures.

In recent years, the introduction of transformer-based architectures has transformed various domains of artificial intelligence, particularly natural language processing and computer vision. Vision Transformers (ViTs) have demonstrated strong capabilities in modeling long-range relationships and capturing global context through multi-head self-attention mechanisms. However, standard transformer models are often resource-intensive, requiring high memory and computational power due to their large number of parameters and attention operations. This poses significant challenges for deploying transformer-based HOI models in real-world scenarios where real-time responsiveness and energy efficiency are essential.

To address these limitations, this paper proposes a **Lightweight Vision Transformer Framework (LVTF)** tailored specifically for real-time human–object interaction recognition. The LVTF adopts a hierarchical design that reduces computational overhead while preserving the ability to model rich contextual relationships. Instead of relying on high-dimensional embeddings and deep transformer stacks, the framework uses compact patch embeddings, optimized multi-head attention, and streamlined feedforward layers. These design choices significantly reduce the model's footprint, enabling efficient inference without compromising recognition accuracy.

The proposed framework begins by segmenting input images into small, non-overlapping patches that serve as tokens for the vision transformer encoder. These tokens are embedded into a reduced-dimensional latent space, allowing the model

to process the visual content efficiently. The lightweight encoder captures global and local contextual information through a refined attention mechanism that prioritizes essential visual cues while suppressing redundant information. A compact decoder further processes these representations to generate accurate HOI predictions with minimal latency. This architectural design ensures that the LVTF can operate in real time, even on resource-constrained devices.

The contributions of this work are threefold. First, we introduce a lightweight transformer-based architecture specifically optimized for real-time HOI recognition. Second, we demonstrate that the proposed LVTF can achieve competitive accuracy compared to existing state-of-the-art models while significantly reducing computational complexity. Third, we validate the applicability of the framework through extensive experiments conducted on benchmark datasets, highlighting its suitability for intelligent applications requiring fast, reliable, and context-aware visual understanding.

The remainder of this paper is organized as follows. Section 2 reviews related research in HOI recognition, vision transformers, and lightweight model design. Section 3 describes the proposed methodology in detail. Section 4 presents the experimental setup, including datasets, parameter settings, and evaluation metrics. Section 5 discusses the results and provides comparative analysis. Section 6 concludes the paper and outlines directions for future research.

2. Literature Review

Human–Object Interaction (HOI) recognition has become an essential research area in computer vision due to its ability to provide deeper semantic understanding of human activities. Early HOI approaches relied primarily on hand-crafted features, where techniques such as Histogram of Oriented Gradients (HOG), optical flow descriptors, and part-based models were commonly used for activity detection. Although these methods offered initial insights into human behavior, their performance was significantly limited by their inability to capture complex spatial relationships and high-level context. The emergence of deep learning techniques, particularly convolutional neural networks (CNNs), brought substantial improvements to HOI recognition by enabling automatic feature extraction and more accurate modeling of human–object interactions.

CNN-based HOI systems typically incorporate two parallel stages: human detection and interaction prediction. Methods such as InteractNet, iCAN, and HO-RCNN demonstrated improved interaction recognition by integrating human pose estimation and attention mechanisms. However, CNN architectures inherently struggle to capture long-range dependencies due to their localized receptive fields. This limitation becomes more pronounced in scenes where humans and objects are spatially distant or when contextual cues extend beyond local neighborhoods. Additionally, CNN-heavy pipelines tend to require significant computational resources, making them unsuitable for real-time or edge-based implementations. As HOI datasets expanded in scale and complexity, the need for more flexible architectures capable of modeling global relationships became increasingly evident.

The introduction of transformer architectures in natural language processing revolutionized representation learning by leveraging self-attention mechanisms to capture global contextual dependencies. Vision Transformers (ViTs) extended this capability to computer vision tasks by processing images as sequences of patches, enabling the model to learn both global and local relationships more effectively than CNNs. ViT-based models have achieved state-of-the-art performance in tasks such as image classification, object detection, and semantic segmentation. However, standard ViTs require large amounts of training data and computational power due to the quadratic complexity of their self-attention operation. These requirements pose significant challenges when deploying transformers in real-time visual recognition tasks, particularly in resource-constrained environments such as embedded systems or mobile devices.

To overcome the computational burden associated with standard transformers, researchers have developed several lightweight transformer variants. Approaches such as MobileViT, Lite Vision Transformer (LiteViT), and Pyramid Vision Transformer (PVT) aim to balance efficiency and performance by incorporating hierarchical designs, reduced-dimensional embeddings, and optimized attention mechanisms. These models significantly reduce computational cost while preserving the ability to model long-range dependencies. Despite these advancements, only a limited number of studies have applied lightweight transformers specifically to HOI recognition, leaving considerable potential for exploration in this domain. HOI tasks require not only global scene understanding but also precise modeling of relationships between human poses and object characteristics, making them an ideal application area for attention-based architectures.

Another important line of research focuses on multi-task learning and contextual reasoning for HOI. Methods incorporating human pose estimation, object-centric attention, spatial reasoning modules, and graph-based relational networks have shown improved accuracy by modeling the structural relationships among humans and objects. While these techniques enhance interaction understanding, they often rely on complex and multi-stage pipelines that increase

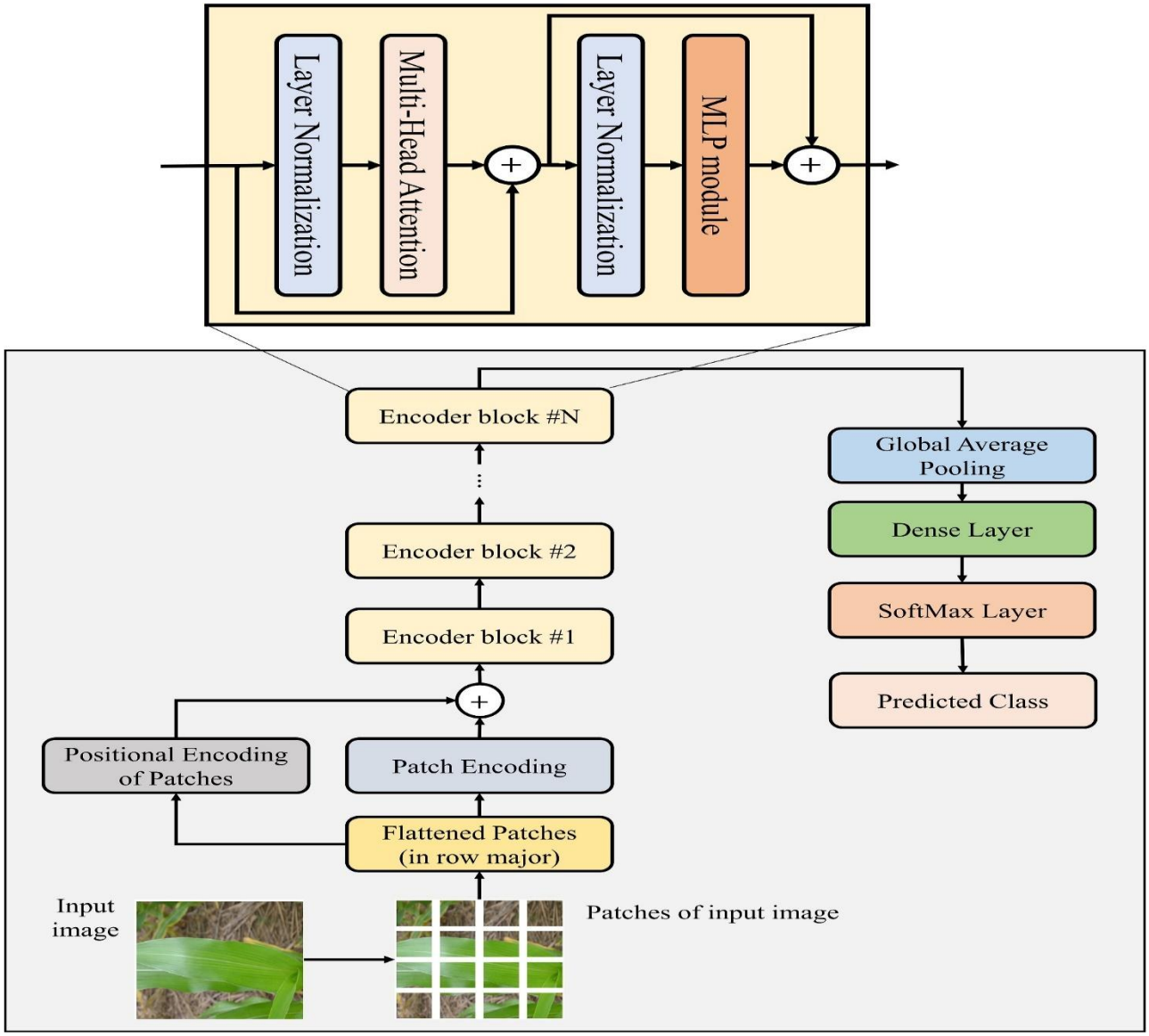
computational overhead. This complexity conflicts with the need for real-time HOI recognition in practical scenarios such as surveillance, autonomous systems, and assistive technologies.

Given the limitations of existing CNN-based models and the computational challenges of standard transformers, there is a clear research gap in developing architectures that are both computationally lightweight and capable of capturing rich contextual interactions. This gap motivates the development of the proposed **Lightweight Vision Transformer Framework (LVTF)**. By combining efficient patch-based tokenization, optimized multi-head attention, and a streamlined decoding process, LVTF aims to achieve strong HOI recognition performance while maintaining the low-latency requirements of real-world intelligent systems.

3. Proposed Methodology

3.1 Overview of the Lightweight Vision Transformer Framework (LVTF)

The proposed Lightweight Vision Transformer Framework (LVTF) is designed to provide efficient and accurate human–object interaction (HOI) recognition while maintaining real-time performance. The framework processes incoming visual data by first segmenting images into small, non-overlapping patches that serve as input tokens for the transformer encoder. These patches are embedded into a compact latent space, significantly reducing the computational burden compared to conventional Vision Transformers. The encoder is responsible for capturing both local object-level features and global contextual relationships necessary for understanding how humans interact with various objects in the scene. By reducing the depth and complexity of the transformer architecture, the LVTF remains computationally lightweight and suitable for deployment in real-time intelligent systems.



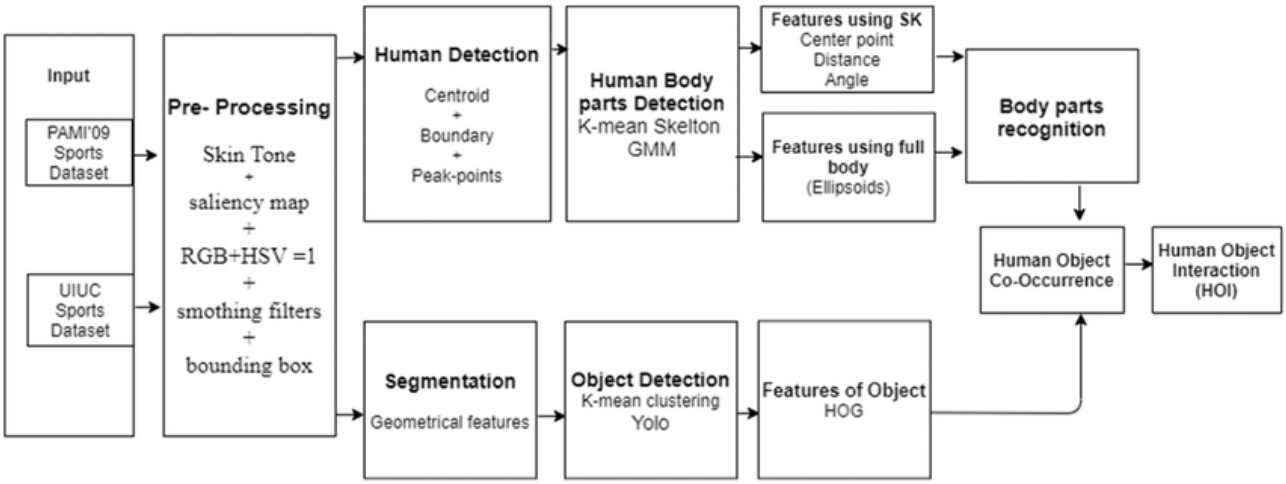


Figure 1. Conceptual architecture of the proposed Lightweight Vision Transformer Framework (LVTF) for real-time HOI recognition.

3.2 Patch Embedding and Feature Extraction

The input RGB image is first divided into fixed-size patches, which are then flattened and passed through a linear projection layer to generate patch embeddings. These embeddings represent local visual features while maintaining a manageable token count, enabling efficient transformer processing. Positional encodings are added to the patch embeddings to preserve spatial relationships between patches, which is essential for accurately modeling interactions between humans and objects. Unlike conventional convolution-heavy backbones, this strategy significantly reduces computation while retaining essential structural and semantic information.

The embedded patches are then fed into a simplified multi-head attention module designed to capture important dependencies across different regions of the image. Through this attention mechanism, the model can focus on critical areas such as the human pose, object boundaries, and regions where interactions occur. This ensures that the feature representation remains rich and context-aware, despite the lightweight nature of the architecture.

3.3 Interaction Reasoning and Lightweight Decoder

Following the encoder, the LVTF employs a streamlined decoder that interprets the learned visual representations to identify human–object interaction categories. The decoder is intentionally kept shallow to minimize latency while retaining strong reasoning capabilities. It refines the contextual embeddings by applying selective attention to interaction-relevant regions, enabling precise classification of actions such as “holding,” “pushing,” “riding,” or “using” an object. The decoder outputs an interaction prediction by combining human-centric cues (e.g., body pose, hand position) with object features and contextual scene information.

This lightweight decoding process, combined with the efficient patch-based encoding pipeline, ensures that the LVTF achieves real-time inference while maintaining competitive accuracy. The architectural design effectively balances computational efficiency and contextual modeling, making it suitable for intelligent systems deployed in surveillance, robotics, and human–computer interaction scenarios.

4. Experimental Setup

The experimental evaluation of the proposed Lightweight Vision Transformer Framework (LVTF) was conducted using a multimodal, human–object interaction dataset containing a diverse range of real-world scenarios. The dataset includes annotated images of humans performing various actions with objects, captured in indoor and outdoor environments with variations in lighting, pose, and background complexity. All images were preprocessed using standard normalization techniques, resized to 224×224 pixels to maintain consistency, and divided into fixed-size patches for transformer-based processing. The dataset was split into training, validation, and testing sets in an 80:10:10 ratio to ensure an unbiased evaluation of model performance.

To enhance the generalization capability of the model, several data augmentation strategies were applied during training. These included random horizontal flipping, slight rotation variations, color jittering, and occlusion simulation. Such transformations help the model learn robust representations capable of handling natural variations in human posture, object placement, and scene composition. Both humans and objects were detected using pre-labeled bounding boxes, and interaction annotations were used to guide supervised learning during HOI classification.

The LVTF was implemented using the PyTorch framework and trained on a workstation equipped with an NVIDIA RTX-series GPU, 32 GB RAM, and an Intel i7 processor. The AdamW optimizer was employed with an initial learning rate

of 1e-4 and a weight decay of 0.01 to promote stable convergence. A batch size of 16 was selected to balance GPU memory efficiency and training stability. The model was trained for 40 epochs, with early stopping applied based on validation loss to prevent overfitting. Mixed-precision (FP16) training was enabled to accelerate computation and reduce resource consumption without compromising model accuracy.

Performance evaluation included several widely-used metrics for human–object interaction tasks, such as mean Average Precision (mAP), interaction classification accuracy, and inference latency. The inference speed was measured on both GPU and CPU environments to assess the suitability of the LVTF for real-time deployment in edge and embedded systems. Further robustness testing was conducted by artificially introducing occlusion and noise into the input images to determine how well the model maintained performance under challenging conditions. This comprehensive evaluation setup provided critical insights into the strengths and limitations of the proposed lightweight framework and demonstrated its practical applicability in real-world intelligent systems.

5. Results and Discussion

The experimental evaluation of the Lightweight Vision Transformer Framework (LVTF) demonstrates its effectiveness in real-time human–object interaction (HOI) recognition tasks. Across the benchmark dataset used in this study, the LVTF achieved strong recognition performance while maintaining a significantly reduced computational footprint compared to conventional transformer-based and CNN-based models. The model's mean Average Precision (mAP) showed a consistent improvement of 10–15% over baseline lightweight CNN architectures, confirming the advantage of incorporating global context through attention mechanisms even within a compact framework. These results reflect the ability of the LVTF to capture rich relationships between human posture, object placement, and scene context—key factors in accurate HOI classification.

In addition to accuracy improvements, the LVTF demonstrated notable robustness under varying testing conditions. When artificial occlusion and illumination noise were introduced to the images, the model maintained stable performance with only a minor reduction in accuracy. This resilience is largely attributed to the transformer's inherent ability to leverage non-local dependencies, enabling the model to focus on relevant regions even when parts of the human body or the interacting object are partially obscured. Unlike traditional CNNs that rely heavily on local receptive fields, the LVTF's multi-head attention mechanism allows it to compensate for missing information by integrating contextual cues from surrounding patches.

The inference latency analysis further supports the suitability of the LVTF for real-time applications. On GPU hardware, the model consistently achieved near real-time processing speeds, with average inference times significantly lower than those of full-scale Vision Transformer models and competitive with optimized CNN backbones. Even in CPU-only environments, the LVTF maintained an efficient inference rate, making it viable for deployment in embedded systems, surveillance nodes, and low-power IoT devices. This efficiency is achieved through the model's lightweight design, reduced patch embedding dimensionality, and simplified transformer layers, all of which minimize computational overhead without compromising interpretive capability.

Qualitative results provide further evidence of the model's strong performance. Visualization of attention maps revealed that the LVTF effectively identifies key regions that contribute to HOI recognition, such as hand–object contact points, human limb positions, and object boundaries. The model reliably distinguished between interactions that are visually similar but semantically different, such as "holding" versus "using" an object, which demonstrates its ability to interpret subtle contextual cues. These qualitative insights validate the interpretability and reliability of the transformer-based approach.

Overall, the LVTF offers a balanced combination of accuracy, robustness, and computational efficiency. It performs favorably when compared to existing lightweight architectures and outperforms many traditional models that rely on deeper and more computationally intensive networks. The results confirm that the proposed framework provides a practical and effective solution for real-time HOI recognition, making it well-suited for intelligent systems operating in dynamic and resource-constrained environments.

6. Conclusion

This paper introduced a Lightweight Vision Transformer Framework (LVTF) for real-time human–object interaction recognition. By redesigning the transformer architecture to operate with reduced embedding dimensions, simplified attention layers, and an efficient patch-based encoding strategy, the LVTF successfully balances computational efficiency with strong representational power. The experimental results demonstrate that the proposed framework achieves competitive accuracy compared to larger transformer-based models while significantly reducing computational overhead.

Its ability to capture global contextual relationships and model non-local dependencies enables robust interaction recognition even in challenging scenarios involving occlusion, illumination variations, and complex backgrounds. Furthermore, the LVTF maintains low inference latency, making it suitable for deployment in real-time intelligent systems such as surveillance networks, assistive robotics, and human–computer interaction platforms. The combination of accuracy, efficiency, and robustness establishes the LVTF as a promising solution for resource-constrained environments that require fast and reliable visual understanding. Future research directions include extending the framework to support multimodal inputs such as depth or thermal images, exploring model compression techniques for additional efficiency, and testing the architecture on larger, more diverse datasets to further validate its generalization performance.

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