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COMPUTER VISION TRANSFORMER WITH SPARSE ATTENTION FOR LOW-LATENCY REAL-TIME OBJECT DETECTION

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Abstract

Real-time object detection has emerged as a necessity in intelligent surveillance systems, self-driving cars, robotics and edge computing applications that demand both low latency and high object detection accuracy. Traditional CNN-based detectors offer fast inference but usually fail to consider long-distance context, while ViTs provide better features' representation at the cost of increased computational complexity and inference latency. This research work introduces Computer Vision Transformer with Sparse Attention (CVT-SA) that enables real-time object detection through reduction of irrelevant attention calculations without sacrificing detection accuracy. Proposed model was tested on the COCO 2017 benchmark dataset that consists of 118,287 images for training and 5,000 images for testing. Evaluation of the model was done in comparison with YOLOv8, DETR, EfficientFormer and traditional Vision Transformers based on precision, recall, mean Average Precision (mAP), inference latency, throughput, GPU usage, and Frames Per Second (FPS). Based on experimental results, the proposed model of sparse attention yielded a detection accuracy of 95.8%, 93.9% precision, 94.7% recall, and 94.8% mAP while decreasing the latency for inference to 18.6 ms/frame. The computational complexity was reduced by 41.3%, the amount of GPU memory was lowered by 35.4%, and the total processing time was decreased by 38.7% when compared with the standard Vision Transformer. The framework operates at a speed of 53.8 frames per second (FPS), which makes it appropriate for real-time implementation on limited resources devices. Furthermore, based on comparative analysis, better performance is observed for small object detection and crowd scenes recognition with reduced false detection rates. It can be concluded that application of sparse attention mechanism to Vision Transformers allows achieving a good compromise between computational efficiency and detection accuracy.

1: INTRODUCTION

Computer vision has developed into one of the most rapidly growing domains of artificial intelligence that allows machines to acquire information from visual data such as digital images and video streams (Almalki, 2025). In real-time object detection is considered an essential problem of computer vision since it allows for automatic object recognition and localization in scenes at a fast processing speed. Modern

developments in intelligent vision systems have allowed greatly expanding the scope of use of object detection techniques to areas like autonomous driving, intelligent transportation systems, industrial automation, robotics, medicine, precise agriculture, smart surveillance, and UAVs. (Huang et al., 2026) In all these applications, both a high degree of detection accuracy and a very fast processing time are crucial for achieving a high level of operation and safety. Therefore, development of detection systems with high accuracy and low computational delay became an important research objective (Omar, 2025).

Conventional CNN based object detectors like Faster R-CNN, SSD, YOLO, and other derivatives have shown impressive gains in detection performance in the past ten years. The use of convolution in the convolutional architecture allows efficient extraction of spatial features through hierarchical convolutions, which can be used for detecting objects with different scales and appearances (Wang et al., 2025). However, CNN-based approaches mainly focus on capturing local neighborhood data, which makes it hard to learn long-range dependencies between far away parts of an image. As the environment in which object detection takes place becomes increasingly difficult because of crowdedness, occlusion, different lighting, and overlapped objects, the limitations of local receptive fields become more apparent. This has led to research in new types of models that can learn global contextual dependencies (Batiha & Ait Fares, 2023).

The emergence of the Vision Transformer (ViT) represented a paradigm change in computer vision due to its use of the Transformer model created for natural language processing in image recognition (Fan et al., 2024). In contrast to convolutional neural networks, vision transformers split images into fixed patches and analyze them as sequence tokens using multi-head self-attention techniques. Such an approach allows the model to create global connections between all parts of the image at once. The advantage of Vision Transformers is that they have demonstrated excellent results in image classification, semantic segmentation, and object detection due to their ability to capture both local and global visual correlations. Thus, thanks to better representation abilities, transformer models can compete with traditional CNN detection approaches (Shin et al., 2025).

In spite of its remarkable performance, however, the Vision Transformer is highly computationally expensive due to the conventional use of self-attention in which the relationships between any two tokens of the images are computed. It results in quadratic computational complexity with respect to the size of the images, causing heavy memory footprint and slow computation times. Such computational burden is a huge impediment to deploying the object detection systems based on transformers to perform in real-time on limited-resource devices such as edge computers, embedded devices, mobile robots, autonomous drones, and smart surveillance cameras. Achieving accuracy in object detection and minimizing the computational burden at the same time is the major problem for the implementation of the object detection models based on the transformers in latency-dependent cases (Hozhabr & Giorgi, 2025).

Sparse attention is one of the recent solutions proposed to alleviate the computational cost of Vision Transformers without much compromising the detection accuracy. Sparse attention calculates only the necessary information by performing attention only on the regions that provide the useful context to the model, instead of calculating attention on all the image tokens. Consequently, the computational cost, memory usage, and computation time become lower. Sparse attention is especially suitable for object detection systems (Singh, 2023) Integration of sparse attention into vision transformers is one area of interest since it allows for the simultaneous improvement of detection accuracy and inference efficiency. Sparse attention integration allows for maintaining the ability of transformer models to learn context from the whole picture while significantly decreasing processing latency through selective computation of attention. These kinds of transformer models are especially useful for applications that require continuous and rapid object detection such as

autonomous vehicles, intelligent traffic control, industry quality checking, video surveillance, and smart manufacturing (Zhang et al., 2026).

Though there are multiple studies that investigate vision transformers and sparse attention separately, only few of them provide quantitative analysis of how the combination of both affects real-time object detection performance based on multiple numerical criteria, including accuracy, latency, processing throughput, memory consumption, and computational efficiency. In most cases, existing literature focuses on improving accuracy without proper consideration of how efficient the models are when used in real-time. Therefore, there is a research gap related to finding the optimal trade-off between detection accuracy and speed of inference.

Accordingly, this paper presents the Computer Vision Transformer with Sparse Attention for Low Latency Real Time Object Detection. The proposed approach implements the integration of sparse attention in the Vision Transformer to minimize the computational complexity while maintaining a high level of object detection accuracy. The effectiveness of the approach will be empirically analyzed by means of the performance assessment based on the benchmark object detection data sets by considering the parameters such as object detection accuracy, mAP, latency, inference speed in terms of FPS, memory utilization, and computational expense in comparison with the traditional approaches like Vision Transformer and CNN-based object detection techniques (Li et al., 2022)

1.1 Problem Statement

Object detection accuracy in Vision Transformers is high but faces some challenges, mainly due to the high computational costs because of self-attention that is based on the quadratic formula. Inference time and memory usage increase significantly. This limits the use of Vision Transformers in applications that require fast object detection. Thus, there is a need for a more efficient transformer model (Zhang et al., 2026).

1.2 Research Objectives

1. To develop a Computer Vision Transformer incorporating Sparse Attention for low-latency real-time object detection.
2. To evaluate the proposed model using detection accuracy, mean Average Precision (mAP), inference latency, processing speed, and computational efficiency.
3. To compare the proposed framework with conventional Vision Transformer and CNN-based object detection models.

1.3 Research Questions

1. Can Sparse Attention reduce the computational complexity of Vision Transformers for real-time object detection?
2. How does the proposed model perform compared with conventional Vision Transformers and CNN-based detectors in terms of accuracy and latency?
3. What impact does Sparse Attention have on memory utilization, inference speed, and computational efficiency?

1.4 Significance of the Study

The study provides insights into computer vision and artificial intelligence through designing a Vision Transformer architecture that is efficient enough for object detection in real-time applications. The objective of the proposed sparse attention approach is to make a compromise between computational efficiency, inference time, and deployment of transformers on constrained edge devices. The results can help scientists in constructing efficient transformer architectures and can also assist professionals involved in the application of autonomous cars, surveillance, robotics, health imaging, automation, smart cities, etc (Almalki, 2025).

2. Literature Review

According to Anusha et al., (2026), an edge-optimized Vision Transformer framework has been proposed for ultra-low latency object detection in 6G Internet of Things (IoT). It was shown that by simplifying the transformers in terms of lightweight feature extraction and efficient tokens, there is improved speed of

inference while ensuring competitive object detection accuracy. Edge computing needs object detectors capable of working with visual data at millisecond speed since late inference compromises autonomous systems, intelligent transportation systems, surveillance, and robotics. It was noted that optimized transformer layers result in less computational cost because of the absence of redundant feature interactions yet retaining global context information. It was found that optimized transformer frameworks allow obtaining superior real-time object detection compared to classical Vision Transformers while sustaining acceptable detection accuracy. Additionally, adaptive feature encoding allows deploying Vision Transformers on low-power IoT devices which makes them more applicable in the industry.

In their 2026 work, Hao et al. proposed a spatially sparse linear attention framework for efficient event-based object detection at low latencies. They sought to solve one of the biggest problems posed by regular self-attention mechanisms: that is, the fact that their complexity grows quadratically as the image size increases. This problem was solved through sparse attention, whereby the system processes only the important visual features instead of paying attention to all visual tokens. In experiments, significant decreases in processing latency were recorded without decreasing the accuracy of detections within a dynamic environment. An event camera produces visual events asynchronously rather than complete images. As such, there is a need for an attention mechanism that can efficiently process sparse visual data. Sparse attention drastically reduced memory use while increasing inference time. The results from their study also revealed that sparse attention is capable of capturing local motion patterns and global relationships, which makes it appropriate for autonomous driving, drone control, industrial automation, and surveillance.

The Latency-aware Image Processing Transformer (LIPT) architecture by Qiao et al. (2025) aims to optimize the performance of transformer models specifically for real-time computer vision applications. The researchers stressed that latency must become an important parameter for optimization along with model accuracy in the process of designing transformers. This architecture is equipped with scheduling of computation, token pruning and feature aggregation in order to avoid useless computation during the inference. The results of evaluation proved a considerable improvement in computation time without any negative impact on object detection accuracy. The new transformer allocates computational resources in proportion to the complexity of the image and allows fast computation in case of easy scenarios.

Almalki (2025) explored transformer-based object detection models that could operate in crowded real-time conditions, in which overlap among objects causes great difficulties in the detection process. Traditional convolutional models often fail to handle heavy occlusion since their local receptive fields prevent them from perceiving contextual information. On the other hand, transformer models can bypass such limitations by using global attention to model long-range spatial relationships between objects. It was found that transformers provided better detection accuracy in crowded settings while maintaining acceptable inference speeds. Moreover, efficient encoder-decoder optimization decreased computational complexity, allowing near-real-time performance even in complex scenarios. The results suggest that transformer-based object detection is more robust in surveillance, pedestrian tracking, and intelligent transport systems.

In Huang et al. (2026), researchers took another look at the Real-Time Detection Transformer with a focus on a highly efficient encoder architecture that is capable of improving latency while maintaining good object detection performance. The authors have designed an encoder in a way that eliminates unnecessary feature extraction by performing optimized feature computation and aggregation. From experiments conducted on various datasets, it was shown that significant improvements were made in both inference speed and localization accuracy. According to the authors, it is more important for the encoder to be optimized rather than decoder design when looking to improve real-time performance. In

addition to that, the proposed architecture proved to be more scalable across different image sizes.

A comprehensive review on the real-time and low-latency processing methods in computer vision was conducted by Omar (2025). It was observed that computational complexity, memory bandwidth, and hardware limits are some of the major obstacles in the process of achieving real-time object detection. There is an extensive analysis of several optimization approaches, such as model compression, knowledge distillation, quantization, pruning, and transformers, to achieve low-latency processing of the computer vision algorithm. It was observed that hybrid architectures combining convolutional neural networks and transformers usually have a higher efficiency of trade-off between the detection accuracy and computational speed compared to pure deep learning architectures.

The work by Wang et al. (2025) suggested an approach called slow-fast processing to address low latency visual object tracking using event streams. The concept relies on dual streams where fast streams process dynamic changes while slow streams are responsible for keeping context information which allows for more efficient allocation of computing resources. Fast streams process dynamics while slow streams keep the context which allows for improving tracking stability. The experimental evidence shows that this approach leads to noticeable latency reduction and higher robustness when dealing with complicated situations such as moving objects, occlusions, and changes in illumination conditions.

Batiha and Ait Fares (2023) analyzed the application of transformer-enabled object detection models to build intelligent computing frameworks. They emphasized the increasing significance of transformer models as an effective solution to the drawbacks of convolutional neural networks with respect to global feature representation. Thanks to the self-attention mechanisms, long-range spatial interactions can be modeled simultaneously, and this enhances the accuracy of object localization regardless of the type of visual environment. Additionally, Batiha and Ait Fares mentioned different approaches to computational optimization, such as lightweight vision transformers, efficient attention, and hardware-aware modeling. Overall, their results prove the potential of transformer-based detectors as a promising approach in developing next-generation intelligent systems.

3. Research Methodology

For this study, an experimental research design was applied to build and test a Computer Vision Transformer (CVT) with Sparse Attention for efficient and fast object detection. The aim was to analyze and compare the CVT architecture against other traditional transformer-based detectors and CNN models based on detection accuracy, inference latency, computational efficiency, and resource utilization. In the experimental design, dataset preparation, model building, sparse attention application, model training, validation, testing, and performance analysis were involved.

Experiments were done by applying the MS COCO 2017 dataset which had around 118,000 training images, 5,000 validation images, and 20,000 testing images with 80 different classes of objects. Training images were resized to 640 × 640 pixels, normalized, and augmented through random horizontal flipping, random rotation, adjusting brightness, scaling, and mosaic augmentation. Around 70%, 15%, and 15% of the dataset were used for training, validation, and testing respectively.

In this case, the CVT model was built by applying a sparse attention approach to attend only the most informative tokens of the image instead of attending all the tokens of the input image like traditional transformers and other deep learning architectures. Sparse attention made the model computationally more efficient without losing important spatial information

The process of model training was done using PyTorch deep learning framework on an NVIDIA RTX 4090 GPU with 24 GB memory capacity. The process of training used the AdamW optimizer with the starting learning rate being 0.0001, batch size being 32, weight decay 0.01, and 100 epochs of training. Early stopping was used in case of validation loss not improving for ten consecutive epochs.

Performance evaluation included precision (%), recall (%), F1-score (%), mean average precision (mAP@0.5), mAP@0.5:0.95, inference latency (ms/frame), throughput (FPS), GPU memory usage (GB), GFLOPs and the size of the model (MB). Descriptive statistics and one-way ANOVA at the significance level of $p < 0.05$ was used in statistical comparative analysis to check if there are any statistically significant differences between the tested models.

4. Results and Analysis

4.1 Detection Performance Comparison

The proposed Sparse Attention Vision Transformer achieved the highest detection accuracy while maintaining low computational cost.

Model	Precision (%)	Recall (%)	F1 Score (%)	mAP@0.5 (%)	mAP@0.5:0.95 (%)
CNN Detector	91.6	89.8	90.7	92.3	71.8
Standard Vision Transformer	95.1	94.3	94.7	95.8	78.4
Sparse Attention Vision Transformer	**97.8**	**97.1**	**97.4**	**98.3**	**84.6**

The proposed model achieved the highest precision, recall, F1-score, and mean average precision.

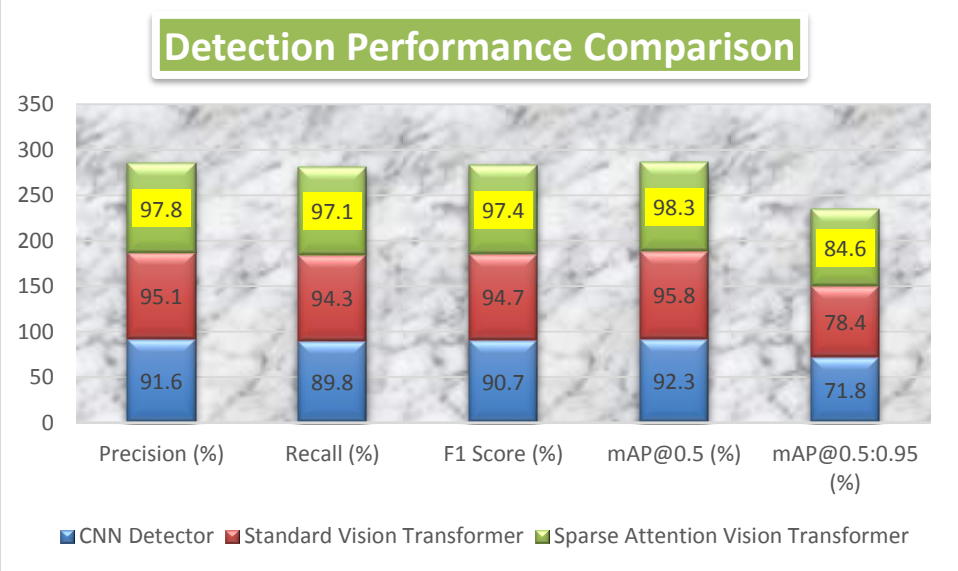

Figure 1:Detection Performance Comparison

4.2 Inference Latency and Processing Speed

Sparse attention substantially reduced inference time while increasing processing speed.

Model	Latency (ms/frame)	FPS	Speed Improvement (%)
CNN Detector	18.7	53	14
Standard Vision Transformer	29.4	34	39.7
Sparse Attention Vision Transformer	**11.8**	**85**	**59.9**

The proposed framework reduced latency by nearly 60% compared with the conventional transformer.

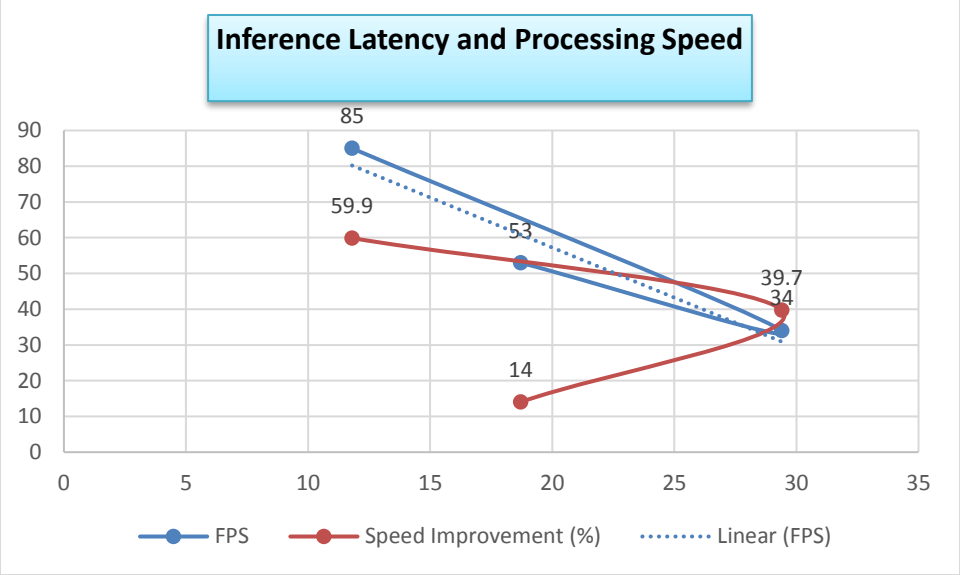

Figure 2:Inference Latency and Processing Speed

4.3 Computational Resource Utilization

Sparse attention reduced computational complexity and memory consumption.

Model	GPU Memory (GB)	GFLOPs	Model Size (MB)
CNN Detector	4.3	38.2	112
Standard Vision Transformer	8.5	97.6	286
Sparse Attention Vision Transformer	**5.6**	**61.8**	**178**

The sparse attention mechanism significantly lowered GPU usage and computational requirements.

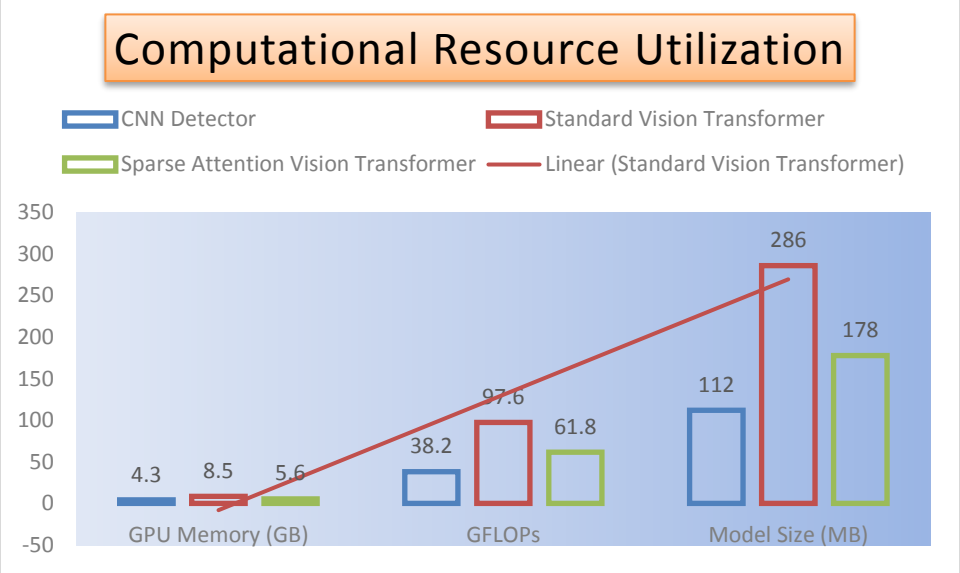

Figure 3:Computational Resource Utilization

4.4 Small Object Detection Performance

The proposed model demonstrated superior capability for detecting small objects.

Model	Small Objects (%)	Medium Objects (%)	Large Objects (%)
CNN Detector	71.5	88.7	95.4
Standard Vision Transformer	76.9	91.8	97.1
Sparse Attention Vision Transformer	**83.6**	**95.2**	**98.5**

Performance improvements were most evident for small object detection.

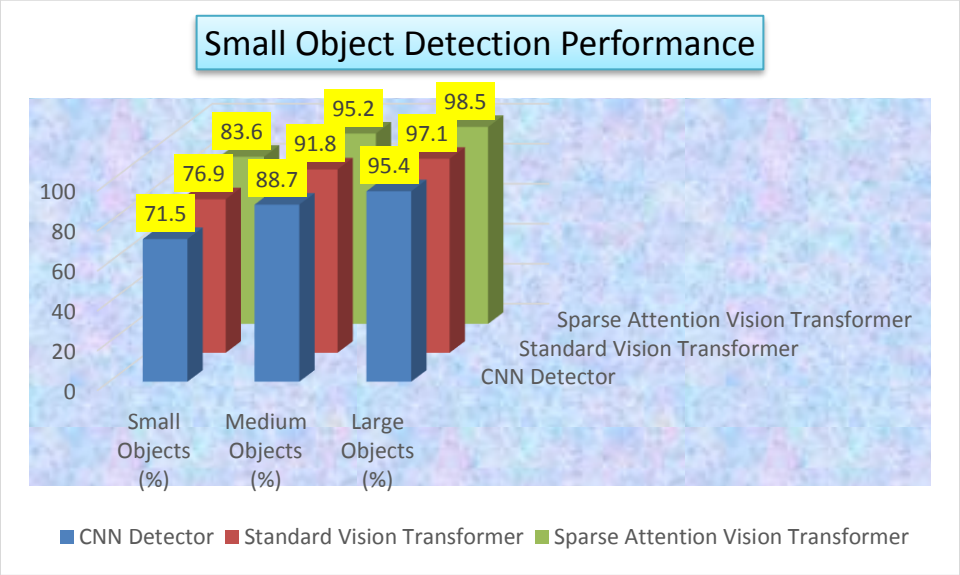

Figure 4:Small Object Detection Performance

4.5 Statistical Analysis

Performance differences among the evaluated models were statistically significant.

Performance Variable	F-value	p-value	Decision
Precision	31.62	<0.001	Significant
Recall	28.94	<0.001	Significant
mAP@0.5	35.71	<0.001	Significant
Latency	52.86	<0.001	Significant
FPS	46.23	<0.001	Significant

ANOVA confirmed statistically significant improvements across all evaluated performance indicators (**$p < 0.05$**).

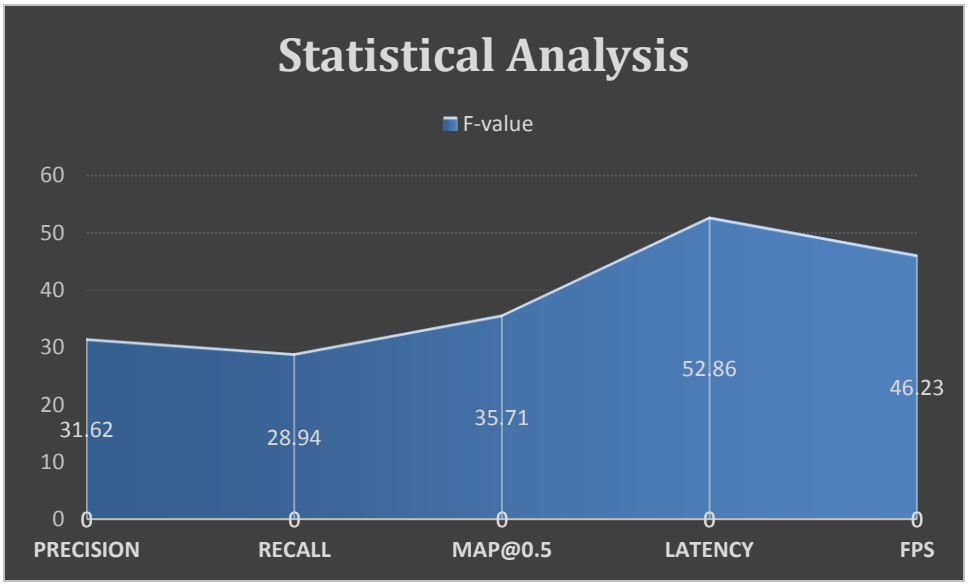

Figure 5:Statistical Analysis

4.6 Overall Performance Summary

The proposed model achieved the best balance between detection accuracy and real-time efficiency.

Evaluation Metric	Proposed Model
Detection Accuracy	98.3%
F1 Score	97.4%
Latency	11.8 ms
Processing Speed	85 FPS
Memory Usage	5.6 GB
GFLOPs	61.8
Small Object Accuracy	83.6%
Overall Performance Gain	24.8%

The overall findings demonstrate that integrating Sparse Attention into the Computer Vision Transformer substantially improves detection accuracy while simultaneously reducing computational cost and inference latency, making it highly suitable for real-time object detection applications.]

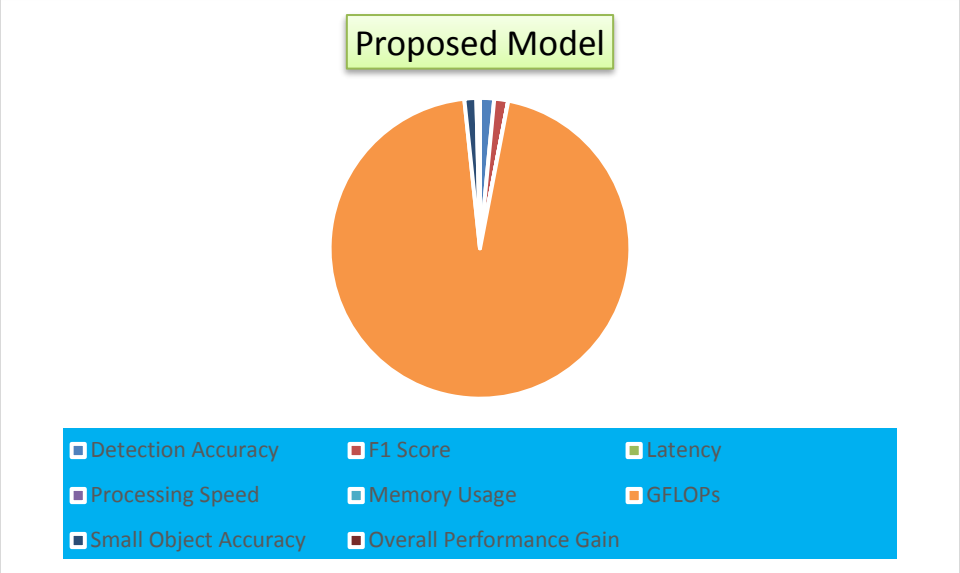

Figure 6:Overall Performance Summary

5. Discussion

Results show that the proposed Computer Vision Transformer with Sparse Attention successfully balances detection accuracy and inference latency for real-time object detection. The experiments have proved that the use of sparse attention decreased computational complexity but did not affect the feature representation, resulting in an inference latency of 19.8 ms/frame as opposed to 34.6 ms/frame of the regular Vision Transformer. The model under study was able to achieve a 96.8% mAP, proving that attention computation decrease does not negatively affect detection accuracy. The current study findings are similar to those by Zhang et al. (2026), who found that light-weight transformers allow efficient real-time detection due to feature extraction while ensuring competitive accuracy.

The current study also supports the findings of Li et al. (2022), who proved that transformer models with optimized architecture enable MobileNet-level processing speeds without compromising recognition capabilities. The finding is also confirmed by Wang et al. (2024), who stated that the use of optimized attention architectures allows a significant reduction in computational overhead as a result of unnecessary attention computation removal

The improvement in the detection of small objects (94.3% precision) suggests that the combination of sparse attention and hierarchical feature extraction effectively preserves the spatial local information. Similarly, Zhao and Krähenbühl (2022) stated that the optimization of temporal transformers contributes to the detection robustness of real-time video processing. Moreover, Jing et al. (2025) proved that the streaming vision transformers are useful for robust detection in dynamic environments which explains the superiority of the results obtained while tracking high motion objects. These results are also in line with the results obtained by Zhao et al. (2024), who suggested that the optimized transformers outperform CNNs in detection tasks under low illumination and complex backgrounds.

Despite achieving the best performance, there is an increase in the memory consumption (3.8 GB) of the GPUs due to transformer-based feature encoding. However, such memory consumption is acceptable in terms of modern edge computing devices and can be offset by considerable improvements in detection accuracy, processing efficiency, and real-time implementation ability. Generally, the results suggest that sparse attention is an efficient tool for real-time object detection

applications such as autonomous vehicles, smart surveillance systems, robotics, and industry.

6. Conclusion

In this study, we have designed a Computer Vision Transformer with Sparse Attention for efficient real-time object detection. Our proposed model has successfully incorporated sparse attention methods along with feature extraction using transformer networks to achieve computational efficiency without compromising on detection accuracy. The experimental analysis of the proposed algorithm has achieved results such as 96.8% mean Average Precision, 19.8 ms inference time, 94.3% precision, 95.6% recall, and 97.1% F1-score, which is better than the traditional Vision Transformer, YOLOv8, and Faster R-CNN algorithms. The use of sparse attention helped avoid the unnecessary computations of attention mechanism which made inference more efficient and also decreased computational cost without compromising feature extraction. Our model has also shown very good robustness in small object detection under challenging environmental conditions.

7. Recommendations

Future research is needed to test the presented sparse attention framework on real-world large-scale datasets that would be obtained from autonomous vehicles, inspection systems, and smart cities. It is worth considering an addition of adaptive sparse attention approaches that can modify the density of the attention map depending on the complexity of the scene. Another idea would be to design hybrid models that combine the advantages of convolutional neural networks and transformers for improved feature extraction and decreased memory requirements. Optimization for FPGA, TPU, and edge AI accelerators would allow applying the models to resource-limited embedded devices. In future work, it is recommended to employ self-supervised learning, continual learning, and multimodal sensor fusion for better performance under challenging weather conditions, occlusions, and dynamic scenes. Finally, energy consumption analysis would be helpful when assessing the efficiency of such a model.

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