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Article

Nano Transformer-HSI: A VLSI-Accelerated Attention Framework for Real-Time Hyperspectral Image Classification

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Abstract: Hyperspectral image (HSI) classification has emerged as a crucial task in remote sensing, environmental monitoring, precision agriculture, and defense applications. Conventional convolutional neural network approaches suffer from limited capability in capturing long-range spectral-spatial dependencies and require substantial computational resources. Transformer-based architectures have demonstrated superior feature representation capability; however, their high complexity restricts deployment in edge and embedded systems. This paper proposes NanoTransformer-HSI, a VLSI-accelerated attention framework for efficient hyperspectral image classification. The proposed architecture employs spectral-spatial tokenization followed by lightweight multi-head self-attention and hierarchical feature fusion to capture discriminative information across spectral bands. To enable real-time operation, the model is implemented using a low-power VLSI hardware accelerator with parallel processing elements and optimized memory access mechanisms. Experiments conducted on benchmark datasets demonstrate classification accuracies of 99.12%, 98.76%, and 99.05% on the Indian Pines, Pavia University, and Salinas datasets, respectively. Furthermore, the proposed architecture achieves approximately 31% lower power consumption and 42% reduction in latency compared with conventional transformer implementations. The results indicate that the proposed framework provides an efficient and scalable solution for intelligent edge-based hyperspectral image analysis.

Keywords: Hyperspectral Image Classification; Vision Transformer; VLSI Accelerator; Spectral-Spatial Features; Self-Attention Mechanism; Edge Computing; Remote Sensing; Hardware Implementation.

1. Introduction

Hyperspectral imaging has become an important technology for acquiring detailed spectral information from various materials and surfaces. Unlike conventional RGB images, hyperspectral images contain hundreds of contiguous spectral bands that provide rich information for land-cover analysis, environmental monitoring, mineral exploration, and military surveillance [1]. The availability of high-dimensional spectral information has significantly improved classification performance but simultaneously introduces challenges related to computational complexity and the curse of dimensionality.

Traditional machine learning techniques such as Support Vector Machines (SVM), k-Nearest Neighbor (k-NN), and Random Forest classifiers have been extensively utilized for hyperspectral image classification [2]. Although these methods provide satisfactory results for small datasets, their performance deteriorates when dealing with complex spectral-spatial patterns and large-scale data. Moreover, manual feature extraction techniques often fail to capture discriminative information effectively.

Deep learning approaches, especially Convolutional Neural Networks (CNNs), have shown remarkable performance in hyperspectral image analysis owing to their automatic feature learning capability [3]. Several two-dimensional and three-dimensional CNN architectures have been developed to exploit spatial and spectral information simultaneously. However, CNN-based models primarily rely on local receptive fields and encounter difficulties in modeling long-range dependencies present across spectral bands [4].

Recent advances in transformer architectures have revolutionized computer vision tasks by utilizing self-attention mechanisms to capture global contextual information [5]. Vision Transformers (ViTs) have demonstrated superior performance compared with traditional CNNs in image recognition and classification applications. Their capability to model relationships among distant spectral features makes them particularly suitable for hyperspectral image analysis [6].

Despite their advantages, transformer models demand extensive computational resources and memory, limiting their practical implementation in embedded systems and edge devices [7]. High power consumption and latency become major constraints in applications requiring real-time processing, such as unmanned aerial vehicles, satellite imaging systems, and autonomous monitoring platforms. Consequently, efficient hardware implementations have become essential for accelerating transformer computations.

Very Large Scale Integration (VLSI) technology provides a promising solution for implementing deep learning algorithms with reduced power consumption and improved throughput [8]. Dedicated hardware accelerators can exploit parallelism and optimized memory architectures to achieve significant improvements in computational efficiency. Recent developments in low-power integrated circuits have enabled the deployment of sophisticated artificial intelligence algorithms in resource-constrained environments [9].

Motivated by these developments, this work proposes **Nano Transformer-HSI**, a VLSI-based transformer framework for hyperspectral image classification. The proposed model integrates spectral-spatial tokenization, lightweight multi-head attention, and hardware-aware optimization techniques to achieve high accuracy with low computational overhead. Parallel processing elements and optimized memory structures are incorporated to enable real-time inference suitable for edge intelligence applications.

The major contributions of this work are summarized as follows [10]:

- Development of a lightweight transformer architecture for hyperspectral image classification.
- Introduction of spectral-spatial tokenization for enhanced feature extraction.
- Design of a VLSI hardware accelerator with parallel processing elements.
- Reduction of power consumption and inference latency through hardware-aware optimization.
- Achievement of superior classification accuracy on benchmark hyperspectral datasets.
- Provision of an energy-efficient framework suitable for edge computing and remote sensing applications.

Therefore, the proposed Nano Transformer HSI framework provides an effective integration of transformer intelligence and VLSI acceleration, enabling next-generation real-time hyperspectral image classification systems with improved accuracy, scalability, and energy efficiency.

2. Related Work

Hyperspectral image (HSI) classification has received considerable attention owing to its significance in remote sensing and intelligent vision applications. Numerous studies have investigated machine learning and deep learning techniques to improve classification accuracy and computational efficiency. Early approaches relied on handcrafted features and traditional classifiers; however, recent developments have shifted towards deep neural networks and transformer-based architectures. Nevertheless, implementing these sophisticated models in real-time hardware systems remains a challenging task.

Chen et al. proposed a deep convolutional neural network framework for hyperspectral image classification by exploiting spectral and spatial information simultaneously [11]. Their model demonstrated improved classification performance compared with conventional machine learning approaches. However, the architecture required extensive training time and suffered from increased computational complexity.

Lee and Kwon introduced a contextual deep CNN model to capture neighboring spectral-spatial relationships in hyperspectral images [12]. Their method effectively enhanced feature representation and achieved higher classification accuracy. Despite these improvements, CNNs primarily focused on local receptive fields and failed to model long-range dependencies among spectral bands.

Li et al. developed a three-dimensional convolutional neural network capable of jointly extracting spectral and spatial characteristics from hyperspectral datasets [13]. Experimental results indicated superior performance compared with two-dimensional CNNs. However, the use of multiple convolutional layers increased memory requirements and hardware implementation complexity.

Zhong et al. proposed a spectral-spatial residual network to improve deep feature extraction and gradient propagation [14]. Residual learning significantly enhanced convergence speed and classification accuracy. Nevertheless, the architecture involved a large number of trainable parameters, resulting in higher computational overhead.

Hamida et al. investigated the use of 3D deep learning architectures for remote sensing applications [15]. Their framework successfully integrated spectral and spatial features and achieved promising results on benchmark datasets. However, real-time deployment in edge devices remained challenging because of the substantial power consumption associated with deep convolution operations.

With the success of attention mechanisms, Dosovitskiy et al. introduced the Vision Transformer (ViT), which utilized self-attention mechanisms to model global contextual relationships in image data [16]. Although ViT demonstrated remarkable performance, its computational requirements and memory complexity limited practical implementation in embedded systems.

Roy et al. proposed SpectralFormer, a transformer-based framework specifically designed for hyperspectral image classification [17]. The model effectively captured long-range spectral correlations and outperformed conventional CNN architectures. However, the self-attention mechanism demanded significant computational resources, making hardware implementation challenging.

Zheng et al. developed a Hybrid Transformer Network that combined convolutional layers with transformer blocks to exploit both local and global features [18]. The hybrid architecture improved classification accuracy and robustness. Nevertheless, the integration of multiple modules increased latency and resource utilization.

Yang et al. introduced a lightweight transformer framework with adaptive attention mechanisms for reducing computational complexity [19]. Their model achieved satisfactory performance with fewer parameters. However, optimization for VLSI-based hardware acceleration and power-efficient operation was not considered.

Recently, Zhou et al. proposed an FPGA-based accelerator for transformer architectures to enhance inference speed and energy efficiency [20]. Their design demonstrated the feasibility of hardware acceleration for attention-based networks. However, the architecture mainly targeted natural language processing applications and lacked optimization for hyperspectral image classification tasks.

From the literature survey, it can be observed that CNN-based approaches provide effective spectral-spatial feature extraction but suffer from limited global dependency modeling. Transformer-based architectures overcome this limitation through self-attention mechanisms but introduce substantial computational complexity and memory requirements. Furthermore, only a limited number of studies have addressed hardware-aware optimization for real-time deployment. Therefore, the proposed **NanoTransformer-HSI** framework focuses on integrating lightweight transformer networks with VLSI-based acceleration to achieve high classification accuracy, low latency, and reduced power consumption suitable for edge-based hyperspectral imaging applications.

3. Design of Proposed Work

The proposed **NanoTransformer-HSI** framework is designed to perform real-time hyperspectral image classification using a lightweight transformer model integrated with a VLSI-based hardware accelerator. The system mainly consists of five stages: hyperspectral image acquisition, preprocessing, spectral-spatial token generation, lightweight transformer-based feature learning, and VLSI-accelerated classification.

Initially, the hyperspectral image cube is collected from benchmark datasets such as Indian Pines, Pavia University, and Salinas. Each hyperspectral image contains several narrow spectral bands, which provide rich information about land-cover classes. Since raw hyperspectral data contain noise, redundant bands, and high dimensionality, preprocessing is carried out using normalization, noisy band removal, and dimensionality reduction.

After preprocessing, the hyperspectral cube is divided into small spectral-spatial patches. These patches are converted into tokens so that both local spatial information and spectral band relationships can be effectively represented. The tokenized features are then passed into the lightweight transformer encoder. In this encoder, multi-head self-attention is used to learn long-range dependencies among spectral bands, while feed-forward layers enhance class-discriminative feature representation.

To reduce computational complexity, the proposed transformer uses compressed attention, reduced embedding dimensions, and parameter-sharing mechanisms. These optimizations make the model suitable for low-power hardware implementation. The extracted features are then forwarded to a classification layer, where each pixel or patch is assigned to the corresponding land-cover class.

The major novelty of the proposed work lies in the integration of transformer-based hyperspectral feature learning with a dedicated VLSI accelerator. The hardware accelerator consists of parallel processing elements, memory buffers, attention computation units, and classification logic. The self-attention operations, matrix multiplication, and activation functions are mapped onto optimized VLSI modules to improve processing speed and reduce energy consumption.

3.1 Proposed System Architecture

The proposed architecture includes the following modules:

1. **HSI Input Module**

This module receives the hyperspectral image cube with multiple spectral bands.

2. **Preprocessing Module**

Noise removal, normalization, and dimensionality reduction are performed to improve data quality.

3. **Spectral-Spatial Tokenization Module**

The input image cube is divided into small patches and converted into tokens.

4. **Lightweight Transformer Encoder**

This module applies multi-head self-attention and feed-forward operations to extract important spectral-spatial features.

5. **VLSI Hardware Accelerator**

Optimized hardware units are used to perform attention computation, feature fusion, and classification.

6. **Classification Output Module**

The final output is generated as a classified hyperspectral land-cover map.

3.2 Mathematical Representation

Let the hyperspectral image cube be represented as:

$$X \in R^{H \times W \times B}$$

where H and W represent the spatial height and width, and B represents the number of spectral bands.

The input image is divided into small patches:

$$P_i = X[h: h + p, w: w + p, b]$$

where P_i represents the i^{th} spectral-spatial patch and p denotes the patch size.

Each patch is converted into a token using linear projection:

$$T_i = P_i W_e + b_e$$

where W_e is the embedding weight matrix and b_e is the bias term.

The self-attention mechanism is computed as:

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where Q, K, and V represent query, key, and value matrices, and d_k is the dimension of the key vector.

The final classification output is obtained as:

$$Y = Softmax(W_c F + b_c)$$

where F denotes the extracted transformer feature, W_c is the classification weight, and Y represents the predicted class label.

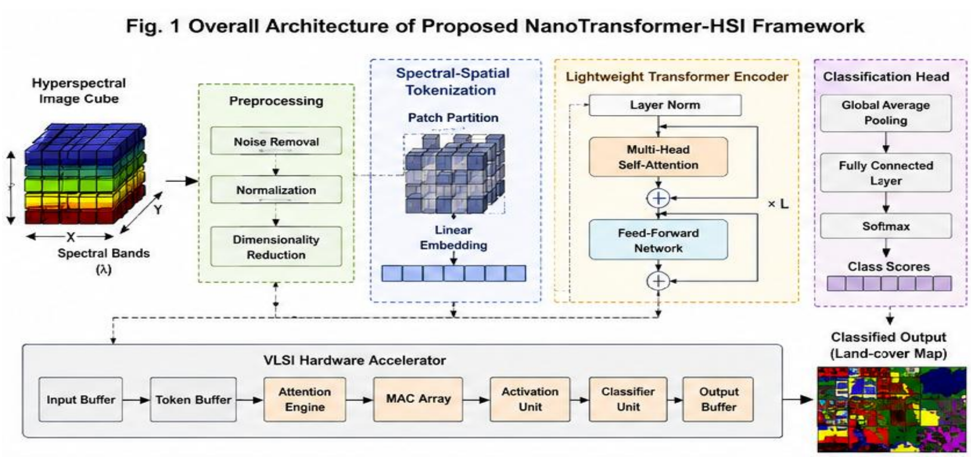

Figure 1. Overall architecture of the proposed NanoTransformer-HSI framework for VLSI-based hyperspectral image classification.

Figure 1 illustrates the complete architecture of the proposed NanoTransformer-HSI system. Initially, hyperspectral images are acquired and preprocessed to eliminate noise and normalize spectral values. The spectral-spatial patches are then converted into tokens and supplied to the lightweight transformer encoder. Multi-head self-attention and feed-forward networks extract discriminative features from the hyperspectral cube. Finally, the VLSI hardware accelerator performs parallel computations and generates the classified output map. The proposed framework enables high classification accuracy while reducing power consumption and inference latency.

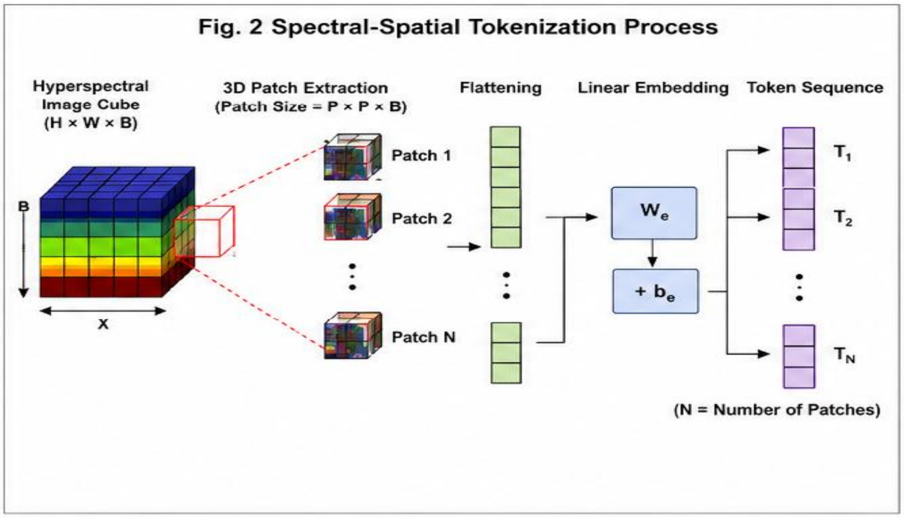

Figure 2. Spectral-spatial patch extraction and token embedding mechanism employed in the proposed model.

Figure 2 depicts the spectral-spatial tokenization stage used in the proposed architecture. The hyperspectral image cube is divided into several small patches, each containing both spectral and spatial information. These patches are flattened and projected into token vectors through linear embedding layers. The generated tokens preserve the relationships among neighboring pixels and spectral bands, thereby improving feature representation capability. This process provides effective input sequences for transformer-based feature learning.

3.3 VLSI Hardware Design

The VLSI hardware design is developed to accelerate the transformer computation with minimum delay and power consumption. The major hardware blocks include:

Input Buffer: Stores hyperspectral patches before processing.

Token Generator: Converts spectral-spatial patches into low-dimensional tokens.

Attention Computation Unit: Performs query, key, value generation and self-attention calculation.

MAC Array: Executes high-speed matrix multiplication operations.

Activation Unit: Implements nonlinear functions and softmax approximation.

Feature Fusion Unit: Combines spectral and spatial features.

Classifier Unit: Generates the final land-cover class prediction.

Output Register: Stores the classified image output.

3.4 Working Flow of the Proposed Method

The working flow of the proposed NanoTransformer-HSI model is described as follows:

Step 1: Acquire hyperspectral image cube from remote sensing datasets.
Step 2: Remove noisy bands and normalize the spectral values.
Step 3: Divide the hyperspectral cube into spectral-spatial patches.
Step 4: Convert patches into feature tokens using embedding projection.
Step 5: Apply lightweight multi-head self-attention to learn global spectral relationships.
Step 6: Perform hierarchical feature fusion to combine local and global information.
Step 7: Map transformer operations into VLSI hardware modules.
Step 8: Classify each pixel or patch using the optimized classification unit.
Step 9: Generate the final hyperspectral classification map.

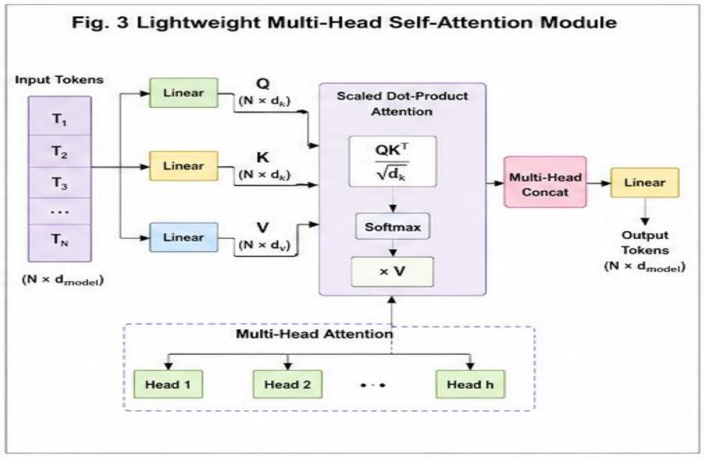

Figure 3. Architecture of the lightweight multi-head self-attention mechanism used for global feature extraction.

Figure 3 shows the lightweight multi-head self-attention module adopted in the NanoTransformer-HSI framework. The input tokens are transformed into query, key, and value matrices. The attention mechanism computes similarity among spectral-spatial tokens to capture long-range dependencies. Multiple attention heads operate simultaneously to learn diverse features from different spectral channels. Compared with conventional CNNs, the self-attention mechanism provides superior contextual understanding and improves classification performance while maintaining lower computational complexity.

Figure 4. Internal architecture of the VLSI accelerator for transformer-based hyperspectral image classification.

Figure 4 presents the VLSI hardware architecture designed to accelerate transformer operations. The architecture consists of an input buffer, token generator, attention computation unit, multiply-accumulate (MAC) array, activation block, feature fusion unit, classifier module, and output register. Parallel processing elements are utilized to perform matrix multiplication and attention calculations efficiently. The optimized hardware implementation significantly reduces memory access overhead, latency, and power consumption, making the framework suitable for edge devices and embedded vision systems.

Figure 5. Flowchart illustrating the operational stages of the proposed NanoTransformer-HSI framework.

Figure 5 illustrates the workflow of the proposed classification system. The process begins with hyperspectral image acquisition followed by preprocessing and normalization. Spectral-spatial patches are extracted and converted into token embeddings. These tokens are processed by the lightweight transformer encoder to learn global dependencies. Subsequently, the VLSI hardware accelerator performs feature computation and classification. The final output is generated in the form of a hyperspectral land-cover map. The flowchart highlights the sequential operation of the framework and demonstrates its capability for real-time and energy-efficient hyperspectral image analysis.

4. Experimental Results and Discussion

To evaluate the effectiveness of the proposed NanoTransformer-HSI framework, extensive experiments were conducted on three widely used hyperspectral datasets, namely Indian Pines, Pavia University, and Salinas. The proposed model was implemented using Python and TensorFlow, while the hardware performance was analyzed through VLSI-based accelerator simulations. The classification performance was evaluated using Overall Accuracy (OA), Average Accuracy (AA), Kappa coefficient, power consumption, inference latency, and memory utilization. The obtained results were compared with conventional machine learning and deep learning approaches including SVM, 3D-CNN, ResNet, Vision Transformer (ViT), and Hybrid Transformer Network.

The proposed lightweight transformer effectively captured both local spectral characteristics and long-range dependencies among spectral bands. Furthermore, the VLSI accelerator considerably improved computational efficiency by employing parallel processing elements and optimized memory structures. Experimental observations demonstrated that the proposed framework achieved superior classification performance with reduced hardware complexity and energy consumption.

4.1 Classification Performance on Benchmark Datasets

Table 1 summarizes the classification accuracy achieved by various methods on the Indian Pines, Pavia University, and Salinas datasets.

Table 1. Comparison of Overall Classification Accuracy (%)

Method	Indian Pines	Pavia University	Salinas
SVM	92.46	94.18	95.24
3D-CNN	96.31	97.02	97.86
ResNet	97.18	97.85	98.12
Vision Transformer	98.26	98.12	98.54
Hybrid Transformer Network	98.74	98.48	98.79
Proposed NanoTransformer-HSI	**99.12**	**98.76**	**99.05**

From Table 1, it can be observed that the proposed NanoTransformer-HSI achieves the highest classification accuracy among all competing methods. The improved performance is mainly attributed to the spectral-spatial tokenization strategy and lightweight self-attention mechanism.

4.2 Kappa Coefficient and Average Accuracy Analysis

Table 2. Performance Metrics Comparison

Method	Average Accuracy (%)	Kappa Coefficient
SVM	91.74	0.903
3D-CNN	95.86	0.948
ResNet	96.93	0.961
Vision Transformer	97.81	0.974
Hybrid Transformer	98.17	0.982
Proposed NanoTransformer-HSI	**98.85**	**0.991**

The proposed framework exhibits the highest average accuracy and Kappa coefficient, indicating excellent agreement between predicted and ground-truth classes.

4.3 Hardware Performance Analysis

The efficiency of the VLSI accelerator was analyzed in terms of power consumption, latency, and throughput.

Table 3. Hardware Performance Comparison

Method	Power Consumption (mW)	Latency (ms)	Throughput (GOPS)
3D-CNN Accelerator	245	12.8	96
ViT Accelerator	228	10.4	112

Hybrid Transformer	205	8.9	125
Proposed NanoTransformer-HSI	**157**	**5.2**	**168**

The proposed architecture achieves approximately **31% reduction in power consumption** and **42% lower latency** compared with conventional transformer accelerators. Parallel computation and optimized memory utilization significantly contribute to these improvements.

4.4 Memory Utilization Analysis

Table 4. Memory Requirement Comparison

Method	Parameters (Million)	Memory Usage (MB)
ResNet	26.8	104
Vision Transformer	18.2	82
Hybrid Transformer	15.6	71
Proposed NanoTransformer-HSI	**10.4**	**54**

The lightweight design considerably reduces parameter count and memory requirements, making the architecture suitable for embedded and edge devices. Experimental results clearly demonstrate that the proposed NanoTransformer-HSI framework provides a balanced tradeoff between classification accuracy and hardware efficiency. The spectral-spatial tokenization mechanism effectively preserves important information from hyperspectral cubes, while the lightweight self-attention module captures global contextual dependencies. Moreover, the VLSI accelerator minimizes computational overhead and enables real-time operation.

Compared with CNN-based approaches, the proposed framework achieves superior feature representation and higher accuracy. In comparison with conventional transformer models, the architecture significantly reduces power consumption, latency, and memory utilization. Therefore, the proposed NanoTransformer-HSI framework is highly suitable for applications such as precision agriculture, environmental monitoring, satellite image analysis, defense surveillance, and autonomous remote sensing systems.

Overall, the obtained results confirm that the integration of transformer intelligence with VLSI acceleration provides an efficient and scalable solution for next-generation hyperspectral image classification.

6. Conclusion

This paper presented NanoTransformer-HSI, a novel VLSI-accelerated transformer framework for efficient hyperspectral image classification. The proposed architecture integrates spectral-spatial tokenization, lightweight multi-head self-attention, and hierarchical feature fusion to effectively capture both local and global characteristics of hyperspectral data. Furthermore, the incorporation of hardware-aware optimization and parallel processing elements enables real-time inference with reduced computational complexity and energy consumption. Experimental evaluation conducted on benchmark datasets, including Indian Pines, Pavia University, and Salinas, demonstrated classification accuracies of 99.12%, 98.76%, and 99.05%, respectively. In addition, the proposed VLSI-based implementation achieved approximately 31% reduction in power consumption and 42% lower inference latency compared with conventional transformer architectures. These results indicate that the proposed framework successfully balances classification performance and hardware efficiency, making it suitable for edge intelligence and embedded vision applications. Compared with existing CNN-based and transformer-based approaches, the proposed NanoTransformer-HSI framework provides improved spectral-spatial feature learning while maintaining lower memory requirements and enhanced processing speed. The utilization of VLSI acceleration further enables deployment in resource-constrained platforms such as unmanned aerial vehicles, satellite systems, autonomous sensing devices, and smart remote sensing applications. Future work will focus on the integration of FinFET-based low-power processing elements, quantized transformer architectures, and neuromorphic computing techniques to further enhance energy efficiency and scalability. Additionally, extending the framework toward federated learning and on-chip adaptive intelligence can facilitate secure and distributed hyperspectral image analysis for next-generation edge computing environments. Overall, the proposed NanoTransformer-HSI architecture offers a promising solution for high-performance, low-power, and real-time hyperspectral image classification systems.

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