VisionGRU: A Linear-Complexity RNN Model for Efficient Image Analysis

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Abstract—Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) are two dominant models for image analysis. While CNNs excel at extracting multi-scale features and ViTs effectively capture global dependencies, both suffer from high computational costs, particularly when processing high-resolution images. Recently, state-space models (SSMs) and recurrent neural networks (RNNs) have attracted attention due to their efficiency. However, their performance in image classification tasks remains limited. To address these challenges, this paper introduces VisionGRU, a novel RNN-based architecture designed for efficient image classification. VisionGRU leverages a simplified Gated Recurrent Unit (minGRU) to process large-scale image features with linear complexity. It divides images into smaller patches and progressively reduces the sequence length while increasing the channel depth, thus facilitating multi-scale feature extraction. A hierarchical 2DGRU module with bidirectional scanning captures both local and global contexts, improving long-range dependency modeling, particularly for tasks like semantic segmentation. Experimental results on the ImageNet and ADE20K datasets demonstrate that VisionGRU outperforms ViTs, significantly reducing memory usage and computational costs, especially for high-resolution images. These findings underscore the potential of RNN-based approaches for developing efficient and scalable computer vision solutions. Codes will be available at https://github.com/YangLiu9208/VisionGRU.

Index Terms—Gated Recurrent Unit, Deep Learning, Image Classification, Semantic Segmentation, Image Analysis

I. INTRODUCTION

Over the past decade, deep learning has revolutionized the field of computer vision [1]-[3]. The advent of Convolutional Neural Networks (CNNs) [4] enabled machines to automatically learn complex patterns from pixel data by stacking convolutional layers. This multi-layer feature extraction approach established the foundation for capturing information at various scales and constructing spatial hierarchies. Later advancements, such as Vision Transformers (ViTs) [5], [6], made significant strides by treating images as sequences of patches and utilizing self-attention mechanisms [7], [8]. This enabled the model to dynamically focus on different regions of the input data, effectively capturing global dependencies and overcoming the limitations of CNNs in modeling long-range interactions. However, these self-attention mechanisms introduce considerable computational complexity, resulting in substantial resource demands, particularly when processing high-resolution images.

To address this issue, several state-space model (SSM)-based approaches have emerged in recent years, such as Mamba [9]. These models introduce dynamic state representations, ef-

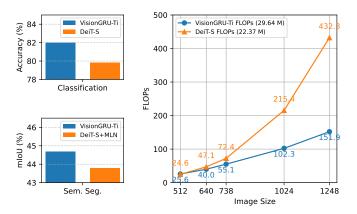


Fig. 1: VisionGRU-Ti achieves higher classification accuracy (82%) and semantic segmentation mIoU (44.7%) compared to DeiT-S models. Moreover, VisionGRU-Ti exhibits significantly lower FLOPs at all resolutions, requiring 151.9 GFLOPs at 1248×1248 compared to DeiT-S's 432.3 GFLOPs, highlighting its computational efficiency.

fectively reducing computational complexity and enhancing processing efficiency in visual tasks. However, compared to convolutional and attention-based models, SSMs still exhibit a performance gap, particularly in image classification, where their performance has yet to meet expectations. Similarly, recurrent neural networks (RNNs) have long been essential for modeling sequential data. Nevertheless, they face limitations in computational efficiency and struggle to scale for large-scale image tasks. Recently, researchers have proposed methods for training RNNs using parallel prefix-scan algorithms, with a simplified version of the Gated Recurrent Unit (GRU) [10], known as minGRU [11], achieving computational efficiency comparable to that of Mamba.

However, the Recurrent Neural Network (RNN) architecture, originally designed for natural language processing (NLP) tasks, is not inherently suited for image processing. First, the number of pixels in an image is much larger than the number of words in most texts, making it challenging to capture finegrained features by simply partitioning the image into fixed-size patches. Second, unlike text, images lack an inherent sequential structure, which makes traditional RNNs ill-suited to handle the unordered, two-dimensional nature of image data. Third,

training RNNs typically relies on backpropagation through time (BPTT), which involves "unrolling" the network across time steps. For large-scale image data, this unrolling becomes computationally expensive, resulting in slower training speeds and increased memory consumption.

To effectively address the challenges outlined above, this study introduces a novel VisionGRU network architecture. By dividing the image into smaller patches at shallow layers and progressively reducing the sequence length while increasing the number of channels through downsampling operations, VisionGRU outputs multi-scale features while ensuring linear growth in computational complexity. Additionally, a bidirectional scanning mechanism is incorporated into a proposed module, 2DGRU, which modifies the RNN into a time-step reverse-symmetric structure. This enables each local feature to simultaneously integrate global contextual information from both preceding and succeeding segments, thereby enhancing the RNN's capacity to capture long-range dependencies. This approach is particularly well-suited for tasks such as semantic segmentation. Moreover, this modification allows each local feature to incorporate comprehensive context information from both the preceding and succeeding parts, further improving the RNN's ability to capture long-range dependencies, which is advantageous for tasks such as semantic segmentation that rely on intermediate feature map outputs. As shown in the Fig. 1, our model exhibits significant advantages in memory efficiency as the resolution increases.

Our contributions are summarized as follows:

- To address the high computational and memory overhead of Transformer models in high-resolution image analysis, we introduce the minGRU structure to eliminate the need for BPTT and enables parallel acceleration. Based on this design, we propose VisionGRU to achieve efficient processing of large-scale features with linear computational complexity.
- To enhance the long-range context modeling capability for 2D features, we design a hierarchical 2DGRU module based on the bidirectional scanning strategy. This approach allows the RNN to effectively capture both local details and global information in 2D spatial domains.
- Experimental results demonstrate that VisionGRU outperforms mainstream ViT models, such as DeiT, on ImageNet and ADE20K datasets. Specifically, with the same number of parameters, VisionGRU achieves 2.2% higher accuracy in classification and 0.9% higher mIoU in segmentation while being 184% more computationally efficient.

II. RELATED WORK

In recent years, deep learning techniques in image classification have experienced a significant shift, transitioning from Convolutional Neural Networks (CNNs) to Transformer models based on self-attention mechanisms. Each approach offers distinct advantages and limitations regarding feature extraction, computational efficiency, and global information capture. This section provides a comprehensive discussion of these methods and their influence on our work.

A. Convolutional Neural Networks (CNNs) and Their Variants

Since the introduction of AlexNet [4], which pioneered the use of CNNs in image classification, architectures such as VGG [12], ResNet [13], and DenseNet [14] have progressively enhanced feature extraction capabilities. These networks have demonstrated outstanding performance in computational efficiency and local feature capture. However, CNNs face limitations in capturing global dependencies, making it challenging to handle complex image structures and long-range relations. Addressing these limitations often requires deeper networks, which increases computational load and training time.

B. Models Based on Self-Attention Mechanisms

Initially applied to natural language processing, Transformer [7] models were later adapted for vision tasks [6]. The Vision Transformer (ViT) [5] utilizes self-attention mechanisms to effectively capture global information from images. However, the computational complexity of ViT scales proportionally with input resolution, leading to significant resource consumption when processing high-resolution images. Variants such as the Swin Transformer [15] mitigates this issue through hierarchical self-attention mechanisms and introduce "Patch Merging" to gradually reduce the spatial dimensions of feature maps, enabling multi-scale feature extraction and lower computational complexity. Nevertheless, the high computational resource requirements for complex tasks remain a significant challenge.

C. Vision Models Based on State Space Models (SSM)

Recently, models based on state-space models (SSMs), such as Mamba [9], have gained attention for their selective state representation mechanisms. These mechanisms dynamically filter out irrelevant information to focus on the most relevant parts of the input sequence. This approach not only reduces computational overhead but also improves processing efficiency. Inspired by their successful application in natural language processing (NLP) tasks [16], many SSM-based vision models have been proposed, such as TranS4mer [17], U-Mamba [18], Vision Mamba (Vim) [19], and VMamba [20].

Vision Mamba is a novel vision backbone based on SSMs. It achieves global modeling through bidirectional SSM and has demonstrated efficient visual representation learning capabilities on datasets like ImageNet. Moreover, its bidirectional scanning strategy inspired the design of our 2DGRU module. Despite the attention garnered by SSM-based vision models, their performance in vision tasks like image classification still lags behind other vision Transformer models.

D. Traditional RNNs and Their Limitations

Traditional Recurrent Neural Networks (RNNs) [21] maintain hidden states across time steps, enabling them to capture temporal dependencies, which makes them well-suited for tasks involving time series and natural language processing. However, basic RNNs face challenges, such as vanishing and exploding gradients [22], when processing long sequences, limiting their ability to model long-term dependencies. To address these issues, enhanced RNN variants like LSTM [23]

and GRU [10] incorporate gating mechanisms. Despite these advances, training RNNs using backpropagation through time (BPTT) remains inefficient for long sequences, leading to their gradual replacement by Transformers, which offer superior parallelization capabilities.

E. Efficiently Trainable RNN Variants

Recently, researchers have proposed novel RNN architectures to improve training efficiency while preserving performance. For example, Orvieto et al. [24] and Beck et al. [25] introduced efficient RNN variants that use complex diagonal recurrence and exponential gating. The Mamba model, derived from state-space models (SSM), achieves efficient training through input-dependent state transition matrices [9], demonstrating strong performance in sequence modeling tasks. Additionally, Feng et al. [26] proposed minLSTM and minGRU, which eliminate the dependence of hidden states on input, forget, and update gates, enabling training with parallel prefix scan algorithms. This simplification reduces the parameter count and significantly improves training speed, with minGRU being approximately 175 times faster than traditional GRU on sequences of length 512. minGRU achieves this efficiency by: (1) removing the dependency on previous hidden states for parallel computation, and (2) eliminating candidate state range constraints (tanh) to ensure temporal independence in outputs. These changes allow minGRU to maintain performance comparable to Mamba and other modern sequence models while achieving linear complexity, which is crucial for long-sequence tasks due to significant resource savings. Like minGRU, some linear attention-based variants also aim to improve training parallelization. Although these approaches have made notable progress in training efficiency and performance, minGRU's design strikes an effective balance between reduced parameters and preserved performance.

III. METHODOLOGY

This section presents the design and implementation details of the VisionGRU model. The core innovation of VisionGRU lies in combining the computational advantages of Recurrent Neural Networks (RNNs) with the ability to process 2D features, enabling efficient global feature capture through the 2DGRU module. The model's overall architecture and key modules are outlined step by step below.

A. Preliminary

1) RNN Theory: Recurrent Neural Networks (RNNs) are network architectures designed to capture temporal information and continuity by propagating states across time steps, thereby maintaining connections between different points in time. The basic RNN formula is as follows:

$$\mathbf{h}_t = \phi(\mathbf{W}_h \mathbf{h}_{t-1} + \mathbf{W}_x \mathbf{x}_t) \tag{1}$$

where \mathbf{h}_t represents the hidden state at the current time step, \mathbf{W}_h and \mathbf{W}_x are learnable parameter matrices, and ϕ is an activation function. Basic RNNs face gradient vanishing and exploding problems when handling long sequences, limiting their ability to model long-term dependencies.

2) GRU Unit: To address the gradient vanishing problem of RNNs, Gated Recurrent Unit (GRU) was introduced. GRU utilizes update and reset gates to regulate information flow, improving the ability to capture long-term dependencies. The GRU equations are as follows:

$$z_t = \sigma \left(\mathbf{W}_z \mathbf{x}_t + \mathbf{U}_z \mathbf{h}_{t-1} \right) \tag{2}$$

$$r_t = \sigma \left(\mathbf{W}_r \mathbf{x}_t + \mathbf{U}_r \mathbf{h}_{t-1} \right) \tag{3}$$

$$\tilde{\mathbf{h}}_t = \tanh\left(\mathbf{W}_h \mathbf{x}_t + \mathbf{U}_h \left(r_t \odot \mathbf{h}_{t-1}\right)\right) \tag{4}$$

$$\mathbf{h}_t = (1 - z_t) \odot \mathbf{h}_{t-1} + z_t \odot \tilde{\mathbf{h}}_t \tag{5}$$

where σ denotes the Sigmoid function, \odot represents elementwise multiplication, z_t is the update gate that controls the carryover of the previous hidden state \mathbf{h}_{t-1} , r_t is the reset gate that modulates the influence of \mathbf{h}_{t-1} in computing the candidate hidden state $\tilde{\mathbf{h}}_t$, and \mathbf{h}_t is the final hidden state at time t, balancing information from \mathbf{h}_{t-1} and $\tilde{\mathbf{h}}_t$ based on z_t .

GRUs effectively mitigate the vanishing gradient problem, but their reliance on backpropagation through time (BPTT) can lead to inefficiencies in handling very long sequences, limiting parallel computation.

3) minGRU Unit: The minGRU is a simplified version of the traditional GRU [10] that achieves efficient parallel training by removing dependencies between hidden states. Specifically, the minGRU eliminates the reset gate from the traditional GRU and removes the dependence of the update gate and candidate hidden state on previous hidden states, while also excluding the tanh activation function to ensure time-scale independence of the output. The minGRU update equation is:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{6}$$

$$z_t = \sigma(\operatorname{Linear}_{d_h}(x_t)) \tag{7}$$

$$\tilde{h}_t = \operatorname{Linear}_{d_h}(x_t) \tag{8}$$

where z_t represents the update gate, and Linear (x_t) is a linear transformation of the input. These modifications reduce the number of parameters and enhance training efficiency [26].

B. VisionGRU Architecture

The overall architecture of VisionGRU is shown in Fig 2. The input image first undergoes initial feature extraction through a shallow convolutional network, with positional embeddings added to preserve spatial information. These features are then processed through a series of 2DGRU modules. Inspired by the Swin model, we incorporate downsampling layers to progressively reduce the spatial dimensions of the feature maps, thereby aggregating high-level semantic information and reducing computational costs. Specifically, the feature map processed by the stem and enhanced with positional encoding serves as the input to the first 2DGRU, denoted as $F \in \mathbb{R}^{H/4 \times W/4 \times D}$, where D is the hidden dimension. Subsequently, these feature maps are treated as a series of tokens in the 2D space, which are fed in both forward and reverse raster scanning orders into the 2DGRU blocks in parallel. Downsampling is applied at specific points to further

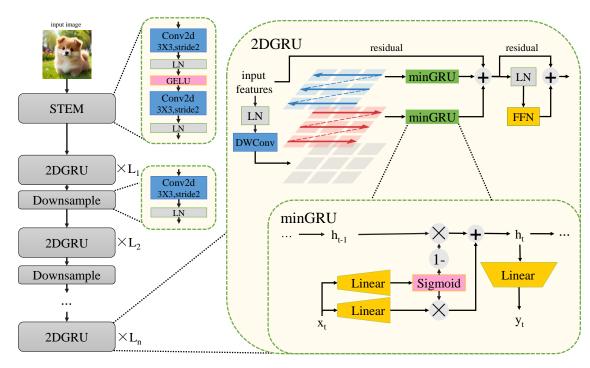


Fig. 2: Overview of the VisionGRU model. It integrates the computational strengths of RNNs and CNNs using a hierarchical 2DGRU module with a bidirectional scanning strategy for efficient global feature capture.

reduce the spatial dimensions and expand the channel width, as detailed in the experimental section. The final output feature $F_{\text{out}} \in \mathbb{R}^{H/32 \times W/32 \times D \times 4}$ is utilized for classification.

C. 2DGRU Module

The 2DGRU module is the core component of the Vision-GRU model, designed to model global spatial dependencies through a bidirectional scanning strategy. The input feature map F_{in} is first normalized using layer normalization, then processed through depthwise convolution and computed using minGRU units. The output features from different directions are aggregated at corresponding positions and passed through a residual connection, followed by an FFN module to produce ther final output feature map arallelism within the 2DGRU module, we expand the recurrence formula for each direction of the minGRU. Assuming the initial hidden state for each minGRU is a zero vector, this assumption eliminates dependencies on previous hidden states, simplifying computation. The output feature at position (i, j), denoted as $f_{(i, j)}^{\text{out}}$, is expressed as:

$$f_{(i,j)}^{out} = f_{(i,j)}^{in} + \sum_{m=0}^{M-1} (y_{\to,m} + y_{\leftarrow,m})$$
 (9)

$$y_{\to,m} = \begin{cases} \prod_{k=m+1}^{L_{i,j}} (1 - z_{k,\to}) \odot z_{m,\to} \odot h_{m,\to} & m \le L_{i,j} \\ 0 & m > L_{i,j} \end{cases}$$
(10)

Output: Output feature map $F_{\text{out}}:(B,H,W,C)$ 1: /* Normalize the input feature map */ 2: $F_{\text{norm}}: (B, H, W, C) \leftarrow \text{Norm}(F_{\text{in}})$ 3: /* Apply depthwise convolution */ 4: $F_{\text{conv}}: (B, H, W, C) \leftarrow \text{DepthwiseConv}(F_{\text{norm}})$ 5: /* Process bidirectionally */ 6: For each path $p \in \{\text{Paths}\}$: $x_p: (B, H \cdot W, C) \leftarrow \min \text{GRU}_p(F_{\text{conv}} \text{ along } p)$ 8: End for 9: /* Aggregate results */ 10: $x \leftarrow \sum_{p} x_{p}$ 11: /* Add residual connection */ 12: $F_{\text{out}}: (B, H, W, C) \leftarrow x + F_{\text{in}}$ return F_{out}

Input: Input feature map $F_{in}:(B,H,W,C)$

Algorithm 1: 2DGRU Block Process

$$y_{\leftarrow,m} = \begin{cases} \prod_{k=L_{i,j}}^{m-1} (1 - z_{k,\leftarrow}) \odot z_{m,\leftarrow} \odot h_{m,\leftarrow} & m \ge L_{i,j} \\ 0 & m < L_{i,j} \end{cases}$$

$$\tag{11}$$

Where:

- fⁱⁿ_(i,j): The input feature at position (i, j).
 f^{out}_(i,j): The output feature at position (i, j).
 M: The total length of the scan sequence.
 L_{i,j}: The index position of the feature at (i, j) in the scan sequence.
 - $z_{k,\rightarrow}, z_{m,\rightarrow}$: Forward update gates, which determine how

new candidate features are accepted in the forward direction.

- $h_{m,\rightarrow}$: The forward candidate hidden state.
- $z_{k,\leftarrow}, z_{m,\leftarrow}$: Backward update gates.
- $h_{m,\leftarrow}$: The backward candidate hidden state.
- $\prod_{k=m+1} (1-z_{k,\rightarrow})$: The residual factor in the forward path, accumulating non-updated (i.e., 1-z) terms from step m+1 to $L_{i,j}$.
- $\prod_{k=L_{i,j}}^{m-1} (1-z_{k,\leftarrow})$: The residual factor in the backward path, accumulating non-updated terms from step $L_{i,j}$ to m-1.

Thus, each output depends solely on the input features, enabling efficient parallelization.

D. Details

The VisionGRU is implemented in two configurations: Base and Tiny. The Base configuration consists of 21 2DGRU blocks, with three downsampling layers inserted. These downsampling layers divide the network into four distinct stages, containing [2, 2, 15, 2] 2DGRU blocks respectively. For the Tiny configuration, the network is adjusted to be lightweight, consisting of a total of 14 2DGRU blocks. Similar to the Base configuration, three downsampling layers are inserted, dividing the network into four stages with the block distribution set to [2, 2, 8, 2]. Both configurations utilize the same principles for feature extraction and downsampling, but the Tiny configuration is optimized for scenarios requiring lower computational costs, making it suitable for lightweight applications.

IV. EXPERIMENT

A. Image Classification

We conducted benchmark tests on the ImageNet-1K dataset [27], which contains 1.28 million training images and 50,000 validation images across 1,000 classes. Our training setup primarily followed DeiT [28]. The input images were resized to a resolution of 224×224 , and the final 7×7 feature maps were average-pooled and passed through a fully connected layer for classification. We used the AdamW optimizer [29] with a momentum of 0.9 and a weight decay of 0.05. Training was performed on eight A800 GPUs for a total of 300 epochs. We used cosine scheduling with a learning rate scaling rule $1 \times 10^{-3} \times \text{batch size}/1,024$. Additionally, we applied Exponential Moving Average (EMA) [30] with a decay rate of 0.9999.

Table I highlights the significant performance gains achieved by VisionGRU when compared to diverse model families, including convolution-based (e.g., ResNet), attention-based (e.g., DeiT), and state-space models (e.g., Vim). Specifically, VisionGRU-Ti attains an 82.0% top-1 accuracy, surpassing both the similarly lightweight DeiT-Ti (72.2%) and Vim-Ti (76.1%). Moreover, with a comparable parameter budget to DeiT-B, VisionGRU-B achieves 83.1% top-1 accuracy—an improvement of 1.3 percentage points over DeiT-B's 81.8%. Notably, these performance gains emerge despite VisionGRU using

TABLE I: Comparison of model architectures in terms of parameter count, input resolution, and ImageNet top-1 accuracy.

Method	#Params	Image Size	Top-1 (%)			
ConvNets						
VGG11	132.8M	224×224	69.1			
ResNet-18 [13]	12M	224×224	69.8			
ResNet-50 [13]	25M	224×224	76.2			
ResNet-101 [13]	45M	224×224	77.4			
ResNet-152 [13]	60M	224×224	78.3			
ResNeXt50-32 × 4d [31]	25M	224×224	77.6			
RegNetY-4GF [32]	21M	224×224	80.0			
Transformers						
ViT-B/16 [5]	86M	384×384	77.9			
ViT-L/16 [5]	307M	384×384	76.5			
DeiT-Ti [28]	6M	224×224	72.2			
DeiT-S [28]	22M	224×224	79.8			
DeiT-B [28]	86M	224×224	81.8			
State-Space Models (SSMs)						
S4ND-ViT-B [9]	89M	224×224	80.4			
Vim-Ti [20]	7M	224×224	76.1			
Vim-S [20]	26M	224×224	80.5			
RNN Models						
VisionGRU-Ti	30M	224×224	82.0			
VisionGRU-B	86M	224×224	83.1			

a straightforward hierarchical RNN structure with minimal architectural optimizations.

A primary reason for these improvements lies in Vision-GRU's bidirectional 2DGRU module, which ensures that each spatial location aggregates information from preceding and succeeding regions in both directions. This global feature fusion alleviates common issues in standard RNNs, where long-range dependencies often vanish through sequential steps. Additionally, VisionGRU's hierarchical downsampling design allows the network to capture multiple feature scales: finer spatial details in earlier layers and more abstract, high-level representations in deeper layers. Consequently, the model balances local detail preservation and global context integration, yielding robust classification performance. Our experimental findings also suggest that the GRU's gating mechanism helps filter out redundant information and focus on salient features—an advantage over pure attention-based methods, which can become computationally expensive when modeling high-resolution inputs.

B. Semantic Segmentation

To further test VisionGRU's generalization ability, we integrated it into a UperNet [33] framework for semantic segmentation experiments on ADE20K. As shown in Table II, UperNet equipped with VisionGRU-Ti achieves a mean Intersection-over-Union (mIoU) of 44.7%, outperforming DeiT-S + MLN (43.8%) and tying closely with more specialized



Fig. 3: The semantic segmentation example from the ADE20K validation set. The left image shows the segmentation result of Swin, while the right image shows the result of our VisionGRU.

TABLE II: Semantic segmentation results on the ADE20K validation set.

Method	Backbone	Image Size	#Params	mIoU (%)
DeepLab v3+	ResNet-101	512×512	63M	44.1
UperNet	ResNet-50	512×512	67M	41.2
UperNet	Vim-Ti	512×512	13M	41.0
UperNet	Vim-S	512×512	46M	44.9
UperNet	Swin-Ti	512×512	60M	44.5
UperNet	DeiT-S + MLN	512×512	58M	43.8
UperNet	VisionGRU-Ti	512×512	60M	44.7

architectures such as Swin-Ti (44.5%). This 0.9% improvement over the DeiT backbone underscores VisionGRU's capability to extract stronger contextual cues, which is crucial for pixellevel tasks. As shown in Figure 3, our model, leveraging the 2DGRU's ability to capture long-range dependencies, is more effective at handling segmentation tasks, such as identifying the curtain in the image, which lacks distinct local features and requires global contextual information for accurate predictions. In contrast, Swin, due to the quadratic complexity of self-attention, divides the image into windows, resulting in limited effective information within each window, which hampers its ability to make accurate predictions in such cases.

Unlike conventional attention-based models, VisionGRU's recurrent design leverages bidirectional 2D scans to encode both local and global spatial information in a memory-efficient way. This advantage becomes increasingly relevant at higher input resolutions, where self-attention can be prohibitively costly. Furthermore, our experiments indicate that Vision-GRU's parallel-friendly architecture—enabled by the minGRU-like structure and prefix-scan training algorithms—makes it straightforward to scale to large images without excessive computation. Consequently, VisionGRU not only shows strong classification accuracy but also delivers competitive results on dense prediction tasks, suggesting its versatility across diverse

vision applications.

C. Discussion and Practical Implications

Overall, VisionGRU's improvements in both image classification and semantic segmentation highlight the effectiveness of combining hierarchical RNN structures with a bidirectional scanning strategy. By integrating multi-scale feature extraction, efficient gating mechanisms, and global spatial context modeling, VisionGRU demonstrates that recurrent networks can remain competitive—and even surpass state-of-the-art transformer-based methods—when specifically redesigned for 2D data processing. From a practical perspective, VisionGRU's linear computational complexity and reduced FLOPs at higher resolutions (Figure 1) present a promising alternative for tasks that require real-time processing or large-scale deployment. We believe these findings not only confirm the resurgence of RNNbased designs in computer vision but also open new directions for more works [34]–[44] (e.g., video analysis, embodied AI, spatial-temporal prediction, medical image analysis and recommendation system) in efficient model architectures.

V. CONCLUSION

This paper introduces VisionGRU, a novel vision backbone architecture that capitalizes on the strengths of RNNs through the incorporation of 2DGRU modules, enabling efficient feature learning and global dependency modeling. The hierarchical structure of VisionGRU, coupled with parallel bidirectional minGRU units, facilitates effective multi-scale feature extraction while maintaining low computational complexity. Extensive experiments on the ImageNet-1K dataset demonstrate that VisionGRU outperforms traditional convolutional neural network architectures in both accuracy and efficiency. The model not only reduces computational overhead significantly but also sets new benchmarks for visual tasks, achieving state-of-the-art performance. Future research can leverage these findings to further optimize the architecture and expand the applicability of VisionGRU to other complex vision tasks.

REFERENCES

- [1] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
- [2] Yang Liu, Guanbin Li, and Liang Lin, "Cross-modal causal relational reasoning for event-level visual question answering," *IEEE Transactions* on Pattern Analysis and Machine Intelligence, vol. 45, no. 10, pp. 11624– 11641, 2023.
- [3] Yushen Wei, Yang Liu, Hong Yan, Guanbin Li, and Liang Lin, "Visual causal scene refinement for video question answering," in *Proceedings* of the 31st ACM International Conference on Multimedia, 2023, pp. 377–386.
- [4] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton, "Imagenet classification with deep convolutional neural networks," *Communications* of the ACM, vol. 60, no. 6, pp. 84–90, 2017.
- [5] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, and Neil Houlsby, "An image is worth 16x16 words: Transformers for image recognition at scale," arXiv preprint arXiv:2010.11929, 2020.
- [6] Salman Khan, Muzammal Naseer, Munawar Hayat, Syed Waqas Zamir, Fahad Shahbaz Khan, and Mubarak Shah, "Transformers in vision: A survey," ACM Computing Surveys (CSUR), vol. 54, no. 10s, pp. 1–41, 2022
- [7] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin, "Attention is all you need," in Advances in neural information processing systems, 2017, vol. 30.
- [8] Yuhong Chou, Man Yao, Kexin Wang, Yuqi Pan, Ruijie Zhu, Yiran Zhong, Yu Qiao, Jibin Wu, Bo Xu, and Guoqi Li, "Metala: Unified optimal linear approximation to softmax attention map," arXiv preprint arXiv:2411.10741, 2024.
- [9] Albert Gu, Marcus Lee, Aditya Grover, Thomas L Paine, and Jascha Sohl-Dickstein, "Mamba: A scalable state-space model for sequence modeling," Advances in Neural Information Processing Systems, 2022.
- [10] Kyunghyun Cho, Bart van Merrienboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio, "Learning phrase representations using rnn encoder-decoder for statistical machine translation," arXiv preprint arXiv:1406.1078, 2014.
- [11] Leo Feng, Frederick Tung, Mohamed Osama Ahmed, Yoshua Bengio, and Hossein Hajimirsadeghi, "Were rnns all we needed?," 2024.
- [12] Karen Simonyan and Andrew Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv preprint arXiv:1409.1556, 2014
- [13] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, "Deep residual learning for image recognition," Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770–778, 2016.
- [14] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger, "Densely connected convolutional networks," Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4700–4708, 2017.
- [15] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo, "Swin transformer: Hierarchical vision transformer using shifted windows," *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 10012–10022, 2021.
- [16] Albert Gu, Karan Goel, and Christopher Re, "Efficiently modeling long sequences with structured state spaces," *International Conference on Learning Representations*, 2021.
- [17] Thanh Nguyen and Xinyu Chen, "Trans4mer: State-space models for vision," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2023.
- [18] Jun Ma, Feifei Li, and Bo Wang, "U-mamba: Enhancing longrange dependency for biomedical image segmentation," arXiv preprint arXiv:2401.04722, 2024.
- [19] Lianghui Zhu, Bencheng Liao, Qian Zhang, Xinlong Wang, Wenyu Liu, and Xinggang Wang, "Vision mamba: Efficient visual representation learning with bidirectional state space model," in *Forty-first International Conference on Machine Learning*.
- Conference on Machine Learning.
 Jian Li, Ming Xu, and Fei Yang, "Vision mamba: A scalable state-space model for vision tasks," arXiv preprint arXiv:2301.01234, 2023.
- [21] Jeffrey L Elman, "Finding structure in time," Cognitive Science, vol. 14, no. 2, pp. 179–211, 1990.
- [22] Yoshua Bengio, Patrice Simard, and Paolo Frasconi, "Learning long-term dependencies with gradient descent is difficult," *IEEE transactions on neural networks*, vol. 5, no. 2, pp. 157–166, 1994.

- [23] Sepp Hochreiter and Jürgen Schmidhuber, "Long short-term memory," Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.
- [24] Axel Orvieto, Krzysztof Choromanski, and Alexandros Papageorgiou, "Efficient rnns with diagonal recurrence," arXiv preprint arXiv:2305.09029, 2023.
- [25] Laura Beck and Chris Thompson, "Complex diagonal recurrence and exponential gating for rnns," *Journal of Machine Learning Research*, 2024
- [26] Liwei Feng, Wei Zhang, and Jisoo Kim, "Minrnns: Simplified recurrent models for efficient sequence modeling," *Neural Information Processing* Systems, 2024.
- [27] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei, "Imagenet: A large-scale hierarchical image database," *IEEE conference on computer vision and pattern recognition*, pp. 248–255, 2009.
- [28] Hugo Touvron, Matthieu Cord, Matthijs Douze, Francisco Massa, Alexandre Sablayrolles, and Hervé Jégou, "Training data-efficient image transformers & distillation through attention," arXiv preprint arXiv:2012.12877, 2021.
- [29] Ilya Loshchilov and Frank Hutter, "Decoupled weight decay regularization," arXiv preprint arXiv:1711.05101, 2017.
- [30] Boris T Polyak and Anatoli B Juditsky, "Acceleration of stochastic approximation by averaging," SIAM journal on control and optimization, vol. 30, no. 4, pp. 838–855, 1992.
- [31] Saining Xie, Ross Girshick, Piotr Dollár, Zhuowen Tu, and Kaiming He, "Aggregated residual transformations for deep neural networks," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 1492–1500.
- [32] Ilija Radosavovic, Raj Prateek Kosaraju, Ross Girshick, Kaiming He, and Piotr Dollár, "Designing network design spaces," *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 10428–10436, 2020.
- [33] Tete Xia, Jianping Wang, Yilun Chen, Zhi Zhang, Dahua Lin, and Gang Yu, "Upernet: Unified perceptual parsing for scene understanding," *European Conference on Computer Vision*, pp. 497–513, 2020.
- [34] Yang Liu, Keze Wang, Guanbin Li, and Liang Lin, "Semantics-aware adaptive knowledge distillation for sensor-to-vision action recognition," *IEEE Transactions on Image Processing*, vol. 30, pp. 5573–5588, 2021.
- [35] Yang Liu, Keze Wang, Lingbo Liu, Haoyuan Lan, and Liang Lin, "Tcgl: Temporal contrastive graph for self-supervised video representation learning," *IEEE Transactions on Image Processing*, vol. 31, pp. 1978– 1993, 2022.
- [36] Jie Ma, Chuan Wang, Yang Liu, Liang Lin, and Guanbin Li, "Enhanced soft label for semi-supervised semantic segmentation," in *Proceedings* of the IEEE/CVF International Conference on Computer Vision, 2023, pp. 1185–1195.
- [37] Yang Liu, Yu-Shen Wei, Hong Yan, Guan-Bin Li, and Liang Lin, "Causal reasoning meets visual representation learning: A prospective study," *Machine Intelligence Research*, vol. 19, no. 6, pp. 485–511, 2022.
- [38] Hong Yan, Yang Liu, Yushen Wei, Zhen Li, Guanbin Li, and Liang Lin, "Skeletonmae: graph-based masked autoencoder for skeleton sequence pre-training," in *Proceedings of the IEEE/CVF International Conference* on Computer Vision, 2023, pp. 5606–5618.
- [39] Yuying Zhu, Yang Zhang, Lingbo Liu, Yang Liu, Guanbin Li, Mingzhi Mao, and Liang Lin, "Hybrid-order representation learning for electricity theft detection," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 2, pp. 1248–1259, 2022.
- [40] Weixing Chen, Yang Liu, Ce Wang, Jiarui Zhu, Shen Zhao, Guanbin Li, Cheng-Lin Liu, and Liang Lin, "Cross-modal causal intervention for medical report generation," arXiv preprint arXiv:2303.09117, 2023.
- [41] Yang Liu, Weixing Chen, Yongjie Bai, Xiaodan Liang, Guanbin Li, Wen Gao, and Liang Lin, "Aligning cyber space with physical world: A comprehensive survey on embodied ai," arXiv preprint arXiv:2407.06886, 2024
- [42] Xinshuai Song, Weixing Chen, Yang Liu, Weikai Chen, Guanbin Li, and Liang Lin, "Towards long-horizon vision-language navigation: Platform, benchmark and method," arXiv preprint arXiv:2412.09082, 2024.
- [43] Yang Liu, Binglin Chen, Yongsen Zheng, Guanbin Li, and Liang Lin, "Fine-grained spatial-temporal mlp architecture for metro origindestination prediction," arXiv preprint arXiv:2404.15734, 2024.
- [44] Yongsen Zheng, Guohua Wang, Yang Liu, and Liang Lin, "Diversity matters: User-centric multi-interest learning for conversational movie recommendation," in *Proceedings of the 32nd ACM International Conference on Multimedia*, 2024, pp. 9515–9524.