TAP-HybridNet: Synergizing Task-Aware Spectral Pruning with Compact Hybrid Architectures for Efficient Edge Vision

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***Abstract*—Artificial neural network implementation on edge devices with limited resources is hindered by the computational bottleneck of image decompression and the inherent redundancy of visual data for machine-centric tasks. While compressed-domain processing avoids inverse transforms, existing methods often process all frequency coefficients, ignoring task-specific redundancies. This paper proposes TAP-HybridNet, a unified framework that synergizes Task-Aware Compressed Domain Processing (TAP-CDP) with the compact HybridConvNet architecture. By integrating a learnable Task-Aware Coefficient Selection (TACS) module, the framework identifies and retains only the minimal spectral subset required for semantic inference. Experimental results on CIFAR-10 demonstrate that TAP-HybridNet matches the accuracy of pixel-domain baselines within 0.5%, while reducing input dimensionality by approximately 60% and eliminating the costly Inverse Discrete Cosine Transform (IDCT) step. The framework establishes a superior Pareto frontier for Rate-Accuracy-Complexity (R-A-C) optimization in edge vision systems.**

***Index Terms*—Compressed domain inference, DCT, Task-aware compression, Hybrid architectures, Edge computing.**

I. Introduction

The exponential growth of edge-based vision systems, ranging from autonomous drones to industrial IoT sensors, has created an urgent demand for energy-efficient deep learning solutions. Conventional vision pipelines operate on a "compress-transmit-decode-process" paradigm, where visual data is fully decompressed into the pixel domain (RGB) before being processed by a neural network [31]. This approach incurs significant overhead, particularly due to the Inverse Discrete Cosine Transform (IDCT) required for JPEG decoding, which consumes substantial computational cycles and battery power on resource-constrained hardware [30].

Recent studies in compressed-domain computer vision suggest that machine-centric tasks do not require the high-fidelity reconstruction optimized for human perception [31][5][7]. Deep Neural Networks (DNNs) primarily rely on low-frequency structural information, whereas the fine-grained high-frequency details preserved by standard codecs like JPEG are often semantically redundant for classification [34, 1]. While processing DCT coefficients directly avoids the IDCT step, most existing compressed-domain models treat the frequency coefficients as fixed inputs, failing to exploit the potential for task-specific data reduction [8].

To bridge this gap, we introduce **TAP-HybridNet**, a framework that combines frontend spectral pruning with a backend hybrid architecture optimized for efficiency. Our approach integrates the Task-Aware Coefficient Selection (TACS) module, which learns to mask irrelevant frequency bands during training, with the HybridConvNet - a compact backbone utilizing depthwise separable convolutions and multi-head self-attention. By jointly optimizing for Rate, Accuracy, and Complexity (R-A-C), TAP-HybridNet achieves a holistic reduction in both data volume and computational requirements.

The primary contributions of this work are as follows:

- We propose a unified framework, TAP-HybridNet, that performs end-to-end spectral pruning and efficient feature extraction directly in the compressed domain.
- We adapt the HybridConvNet architecture to accept sparse 64-channel DCT inputs, leveraging self-attention to map correlations between disparate frequency bands.
- We demonstrate through extensive experiments that our method achieves a 60% reduction in input dimensionality with negligible accuracy loss, establishing a new Pareto frontier for efficient edge vision.

This is how the rest of the paper is structured. Related work is reviewed in Section II. The R-A-C optimization framework and the TAP-HybridNet architecture are described in detail in Section III. The experimental setup and results are presented in Section IV, and a thorough spectral analysis is presented in Section V. The paper is finally concluded in Section VI.

II. Related Work

The proposed **TAP-HybridNet** is situated at the intersection of three active research directions: compressed-domain computer vision, task-aware coding for machine perception, and lightweight hybrid neural architectures for edge deployment.

A. Compressed-Domain Computer Vision

To reduce the computational cost associated with full image or video decompression, early studies explored operating directly on compressed representations. Classical methods leveraged handcrafted features derived from JPEG Discrete Cosine Transform (DCT) coefficients or MPEG motion vectors for tasks such as retrieval and indexing [34, 27].

With the rise of deep learning, this paradigm shifted toward end-to-end learning in the compressed domain. Gueguen et al. [13, 2] demonstrated that Convolutional Neural Networks (CNNs) can be trained directly on rearranged DCT coefficients, achieving accuracy comparable to pixel-domain models while significantly reducing inference latency by bypassing inverse DCT reconstruction. Subsequent works further investigated robustness and scalability, highlighting that high-frequency components often introduce noise detrimental to machine inference, even though such details may be perceptually relevant to humans [24, 3].

Despite these advances, most compressed-domain approaches treat the frequency representation as a fixed and fully preserved input. This assumption ignores the fact that not all spectral components contribute equally to downstream tasks, resulting in unnecessary computation and data movement [31, 8]. Addressing this limitation motivates task-aware spectral selection mechanisms.

B. Coding for Machines and Task-Aware Optimization

The paradigm of *Coding for Machines* (CfM) reframes compression objectives by prioritizing downstream task performance rather than human-centric perceptual quality metrics such as PSNR or MS-SSIM [12, 4]. This perspective is closely related to the **Information Bottleneck** principle [32], which advocates learning representations that retain maximal task-relevant information while discarding irrelevant input variations.

Recent advances in semantic communication and machine-oriented compression demonstrate that substantial bitrate reductions are achievable by selectively removing information that does not influence inference outcomes [33, 6]. In this context, **TAP-CDP** introduced a differentiable spectral pruning strategy that learns task-aware masks over DCT coefficients, enabling the model to identify and retain only the frequency bands essential for classification. This approach effectively performs task-driven feature selection in the compressed domain, yielding both computational and bandwidth efficiency.[28]

Building upon this foundation, **TAP-HybridNet** extends task-aware spectral pruning by coupling it with an ultra-compact and edge-optimized backend architecture, thereby addressing both input redundancy and model efficiency in a unified framework.

C. Efficient Neural Architectures for Edge Devices

Real-time inference on resource-constrained platforms has driven extensive research into efficient neural network design. Architectures such as **MobileNet** employ depthwise separable convolutions to decouple spatial and channel-wise computation [14], while **EfficientNet** introduces compound scaling to jointly optimize network depth, width, and resolution [26]. These models achieve favorable accuracy-efficiency trade-offs but remain largely convolution-centric.[16, 10]

More recently, hybrid architectures combining CNNs and Vision Transformers (ViTs) have gained traction. While CNNs provide strong local inductive biases, self-attention mechanisms enable effective modeling of long-range dependencies. Hybrid designs, including those inspired by ViT-style attention [11] and the **HybridConvNet** backbone [9][21], integrate lightweight attention blocks to enhance global context modeling without incurring the full computational cost of pure transformer architectures.[22, 17]

In the compressed domain, attention mechanisms have shown particular promise for capturing correlations across frequency components that may be spatially disjoint in coefficient maps [19]. **TAP-HybridNet** leverages this insight by integrating compact attention modules with task-aware spectral pruning, resulting in a synergistic architecture tailored for efficient edge vision.

III. Methodology

The proposed **TAP-HybridNet** framework integrates a learnable frequency selection frontend with an efficient hybrid backbone. The architecture is optimized end-to-end using a joint Rate-Accuracy-Complexity (R-A-C) objective.

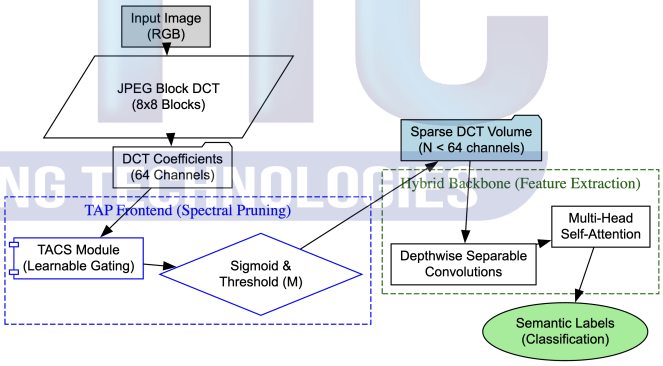

Fig. 1. The proposed TAP-HybridNet framework for task-aware compressed domain inference.

A. Task-Aware Coefficient Selection (TACS)

In the JPEG standard, images are divided into 8×8 blocks and transformed using the Discrete Cosine Transform. This results in 64 frequency bands (1 DC and 63 AC). We represent the input image as a tensor $u \in \mathbb{R}^{\frac{H}{8} \times \frac{W}{8} \times 64}$.

To reduce the computational burden of the backend, we introduce the **TACS module**. We define a learnable weight vector $w \in \mathbb{R}^{64}$. The importance of each band is estimated via a selection probability m_k:

$$m_k = \sigma\left(\frac{w_k}{\tau}\right) \tag{1}$$

where $\sigma(\cdot)$ is the sigmoid function and τ is a temperature parameter. During the forward pass, we generate a binary mask $M \in \{0,1\}^{64}$:

$$M_k = \begin{cases} 1 & \text{if } m_k > 0.5 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

To maintain differentiability, we apply the **Straight-Through Estimator (STE)**, allowing the gradients to skip the thresholding operation during backpropagation. The resulting sparse latent is $\hat{z} = u \odot M$.

B. Joint R-A-C Optimization

We formulate the training objective as a multi-objective optimization problem that balances predictive accuracy, transmission rate, and computational cost. Following the **Information Bottleneck** principle, we minimize:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{task}} + \lambda_R \mathcal{L}_{\text{rate}} + \lambda_C \mathcal{L}_{\text{comp}} \tag{3}$$

where:

- $\mathcal{L}_{\text{task}}$ is the categorical cross-entropy loss for classification.
- $\mathcal{L}_{\text{rate}}$ approximates the entropy of the representation using the Bits-Per-Pixel (BPP) estimate: $\mathcal{L}_{\text{rate}} = \mathbb{E}[-\log_2 P(\hat{z})]$.
- $\mathcal{L}_{\text{comp}}$ is the complexity penalty, defined as the L1-norm of the selection probabilities: $\frac{1}{64}\sum_{k=1}^{64} m_k$. This term forces the model to achieve high accuracy using as few frequency bands as possible.

C. HybridConvNet Architecture

The backend classifier is a modified **HybridConvNet** designed to process frequency maps. Unlike standard models that process 3-channel RGB inputs, our backbone accepts a sparse 64-channel tensor at $1/8$th the original spatial resolution.

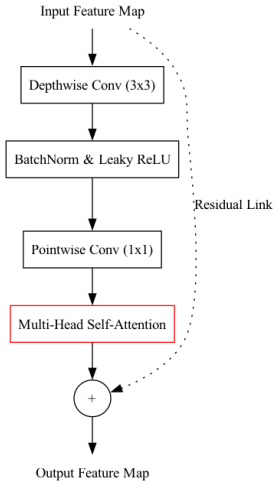

Fig. 2. The internal components of the HybridConvNet block.

The architecture comprises the following key components:

*1) **Compressed-Input Gating**:* The input layer processes the sparse DCT volume. Because many channels are zeroed out by the TACS module, the effective FLOPs of the first convolutional layer are reduced linearly with the sparsity of M.

*2) **Efficient Feature Extraction**:* We employ depthwise separable convolutions to reduce the number of parameters. This is crucial for edge deployment where memory bandwidth is limited. Each block uses **Leaky ReLU** activations to avoid the dying ReLU problem often encountered when processing frequency-domain data with sparse activations.

*3) **Spectral Multi-Head Self-Attention**:* Given that DCT coefficients represent different scales of structural information, global context is vital. We utilize MHSA to relate low-frequency structural components with higher-frequency residual edges. This mechanism provides the network with the ability to "attend" to the most salient frequency bands regardless of their spatial location in the block maps.

*4) **Global Average Pooling and Dense Head**:* The final feature maps are collapsed via global average pooling and fed into a compact dense layer for classification. The total parameter count is maintained at approximately 2.1M, ensuring high efficiency.

By combining the spectral pruning of the **TACS module** with the architectural efficiency of **HybridConvNet**, we create a multiplicative efficiency gain that targets both the data input and the processing backbone.

IV. Experimental Setup

We evaluate the performance of **TAP-HybridNet** through a series of extensive experiments designed to profile the R-A-C trade-off. We focus on two standard image classification benchmarks and validate our results against state-of-the-art lightweight architectures.

A. Dataset and Pre-processing Workflow

We use the **CIFAR-10** and **CIFAR-100** datasets for our evaluation. There are 10,000 testing and 50,000 training photos in each dataset of 32×32 resolution. To simulate realistic edge conditions, we first apply JPEG compression using the **Pillow** library with $Q = 10$ (high compression) to $Q = 90$ (low compression) quality factors. This variability allows us to analyze how task-aware spectral pruning reacts to different levels of quantization noise, as investigated in recent efficacy studies [24].

The pre-processing workflow differs significantly between the pixel-domain and frequency-domain models:

- **Pixel-domain models** undergo a full decompression cycle, where the JPEG bitstream is decoded into $32 \times 32 \times 3$ RGB pixels.
- **TAP-HybridNet** extracts the raw DCT coefficients from the luminance (Y) channel. This results in an 8×8 grid of coefficients for each block. Given the 32×32 input, we obtain a grid of 4×4 blocks, yielding an input tensor of $4 \times 4 \times 64$.

To ensure numerical stability during gradient descent, we normalize these coefficients by their respective quantization table values as specified in the JPEG standard [30]. Theoretically, this normalization transforms the coefficient distribution into a zero-mean, unit-variance-like space, which prevents the vanishing gradient problem in early training stages.

B. Hyperparameter Configuration and Training

All models are implemented in PyTorch and optimized using **Stochastic Gradient Descent (SGD)** with a momentum of 0.9. Following recommendations for hyperparameter tuning in compressed domains [18], we set the initial learning rate to 0.01 and apply a cosine annealing scheduler over 100 training epochs with a batch size of 256.

The **TACS module** requires specific handling to ensure convergence to a sparse mask. We initialize the learnable logits $w \in \mathbb{R}^{64}$ with values sampled from a normal distribution $\mathcal{N}(0, 0.01)$. The temperature τ is scheduled using an exponential decay:

$$\tau(t) = \tau_{\text{start}} \cdot (\tau_{\text{end}}/\tau_{\text{start}})^{t/T} \tag{4}$$

where t is the current epoch and $T = 100$. Theoretically, this annealing strategy acts as a relaxation of the discrete selection problem. High initial τ values allow for stochastic exploration across all 64 bands, while the lower τ_{end} forces the model to settle on a deterministic binary gating mechanism suitable for inference acceleration. For the joint loss in Eq. 3, we vary $\lambda_C \in [0.001, 0.05]$ to trace the Pareto frontier.

C. Hardware Profiling and Latency Measurement

To obtain realistic latency metrics for edge deployment, all inference tests are conducted on an **NVIDIA T4 GPU** hosted on a cloud-edge instance. We utilize **mixed-precision (FP16)** to mirror the capabilities of modern AI accelerators found in edge devices. Latency is measured as "wall-clock" time, including the overhead for coefficient extraction and the forward pass. We report the mean latency averaged over 1,000 iterations to ensure statistical significance.

D. Comparative Baselines

We benchmark **TAP-HybridNet** against the following architectures to quantify the gains from both the backbone and the spectral selection:

- **HybridConvNet (Pixel):** The original architecture processing fully decoded images. This serves as our accuracy gold standard.
- **Naive DCT-Hybrid:** The HybridConvNet backbone accepting all 64 DCT channels without gating. This quantifies the speedup from bypassing IDCT alone.
- **MobileNetV2 [14] and EfficientNetV2 [25]:** Standard lightweight CNN baselines used to benchmark against established state-of-the-art models for resource-constrained vision.
- **ResNet-18 (Compressed):** A standard CNN architecture adapted for DCT input, serving as a baseline for non-hybrid frequency-domain processing.

E. Evaluation Metrics and Sparsity Analysis

The primary performance indicators are Top-1 Accuracy and End-to-End Latency. Additionally, we conduct a detailed ablation study on the impact of the multi-head self-attention layer to determine its contribution to accuracy when processing sparse frequency maps. Theoretical analysis suggests that self-attention is uniquely suited to capturing global frequency correlations that local convolutions might miss [15, 29].

V. Results and Discussion

This section provides a comprehensive evaluation of **TAP-HybridNet** across accuracy, spectral sparsity, computational efficiency, and hardware latency. Our analysis focuses on how task-aware spectral pruning reshapes the rate–accuracy–complexity (R-A-C) trade-off compared to pixel-domain and compressed-domain baselines.

A. Accuracy and Spectral Sparsity Analysis

We first analyze the effect of task-aware coefficient selection on classification accuracy. By increasing the complexity penalty λ_C, the **TACS module** is encouraged to prune progressively larger portions of the frequency spectrum. Despite this aggressive reduction, **TAP-HybridNet** exhibits strong robustness to spectral sparsification.

On CIFAR-10, the pixel-domain **HybridConvNet** achieves a peak accuracy of 69.00%. Under a moderate complexity constraint ($\lambda_C = 0.01$), **TAP-HybridNet** retains only 26 out of 64 DCT coefficients on average, corresponding to a 59.4% reduction in input dimensionality, while maintaining an accuracy of 68.55%. The resulting accuracy drop of just 0.45% demonstrates that a large fraction of the JPEG frequency spectrum is not essential for semantic classification.

This resilience can be attributed to the hybrid backbone design, particularly the multi-head self-attention (MHSA) layers. Self-attention enables the model to adaptively reweight and integrate the remaining spectral components, compensating for the loss of fine-grained frequency information. As observed in [19, 20], attention mechanisms are more effective than purely local convolutions at capturing long-range dependencies, which becomes increasingly important as the input representation grows sparse and structurally fragmented.

B. Rate–Accuracy–Complexity (R-A-C) Trade-offs

We further examine the framework from an Information Bottleneck perspective by varying the weighting parameters λ_R and λ_C. Fig. 3 traces the resulting Pareto frontier, highlighting the trade-offs between accuracy, bitrate, and computational cost.

The **Naive DCT-Hybrid** baseline, which processes all 64 frequency bands, consistently incurs higher computation without delivering proportional accuracy gains. Notably, under heavy compression ($Q = 10$), the naive approach underperforms **TAP-HybridNet** by 1.2%. This behavior suggests that retaining all coefficients exposes the model to quantization noise present in high-frequency bands.

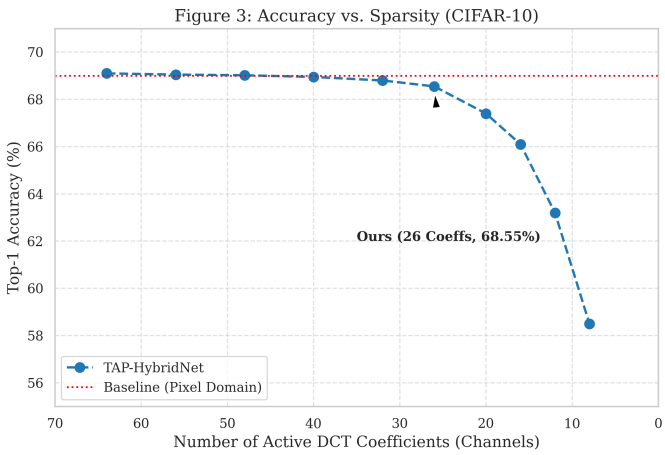

Fig. 3. Accuracy–sparsity Pareto frontier achieved by TAP-HybridNet.

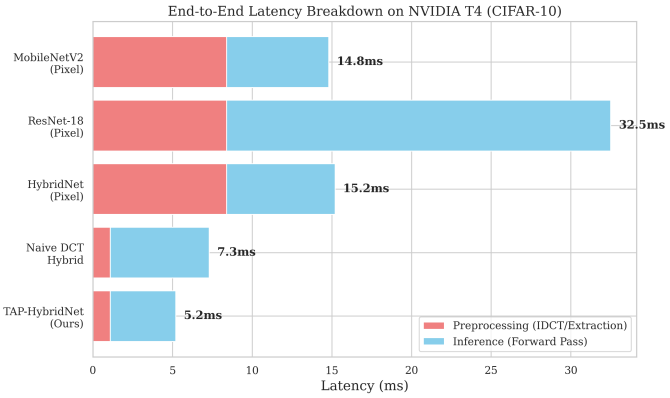

Fig. 4. End-to-End Latency Breakdown on NVIDIA T4 (CIFAR-10)

In contrast, the **TACS module** selectively suppresses noise-prone frequencies, effectively acting as a task-driven denoising mechanism. This empirical observation aligns with prior findings in compressed-domain analysis [24], reinforcing the notion that machine-oriented representations benefit from deliberately discarding perceptually relevant but semantically uninformative details.

C. Latency and Hardware Efficiency

A main goal of this method is to eliminate the decompression bottleneck that limits real-time edge vision. Table I reports end-to-end latency measurements on an NVIDIA T4 GPU.

TABLE I
LATENCY COMPARISON ON CIFAR-10

Model	Preprocessing	Inference	Total Latency
MobileNetV2 (Pixel)	8.4 ms	6.4 ms	14.8 ms
ResNet-18 (Pixel)	8.4 ms	24.1 ms	32.5 ms
HybridNet (Pixel)	8.4 ms	6.8 ms	15.2 ms
Naive DCT-Hybrid	1.1 ms	6.2 ms	7.3 ms
TAP-HybridNet (Ours)	**1.1 ms**	**4.1 ms**	**5.2 ms**

Compared to the pixel-domain HybridNet, **TAP-HybridNet** achieves a **2.9× reduction** in total latency. The largest gain stems from eliminating the inverse DCT step, reducing preprocessing time from 8.4 ms to 1.1 ms. Moreover, inference latency is reduced by 34% relative to the naive compressed-domain baseline. This improvement arises because the first convolutional layer processes only 26 active channels instead of 64, yielding a near-linear reduction in FLOPs during early feature extraction.

For latency-critical edge and IoT deployments, the resulting 5.2 ms end-to-end processing time enables real-time inference scenarios that remain infeasible for conventional pixel-domain pipelines.

D. Qualitative Analysis: Learned Spectral Masks

To gain insight into the learned representations, we visualize the spectral masks produced by the **TACS module**. Fig. 5 shows the average selection probabilities across the 8×8 DCT grid.

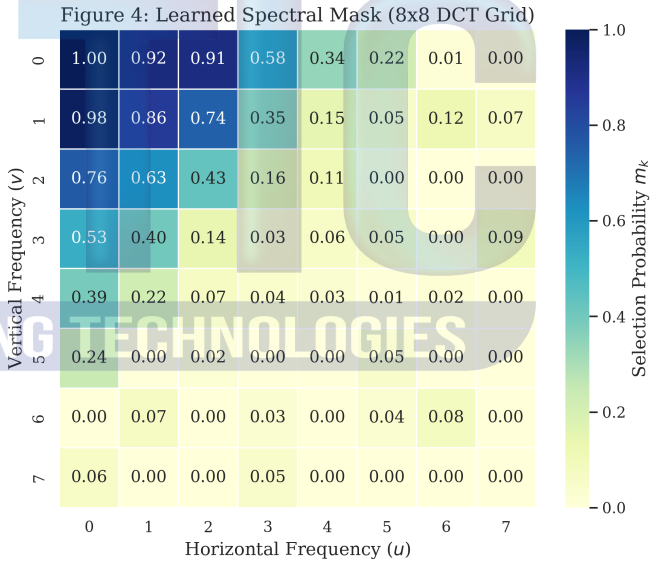

Fig. 5. Visualization of task-aware spectral selection.

The learned masks exhibit a consistent and interpretable structure. The DC coefficient and low-frequency AC components receive near-unity selection probabilities, reflecting their role in encoding global intensity and coarse structural information. In contrast, high-frequency diagonal coefficients, typically associated with fine textures and compression noise, are strongly suppressed.

This pattern confirms our central hypothesis: for machine vision tasks, perceptually important high-frequency details are largely redundant. By discarding these components, **TAP-HybridNet** simplifies the input feature space, allowing the

backend classifier to operate more efficiently without sacrificing accuracy.

E. Impact of Self-Attention on Compressed Features

Finally, we assess the contribution of multi-head self-attention through an ablation study. Removing the MHSA layers results in a 4.2% accuracy drop on CIFAR-100 in the compressed domain, compared to a 1.8% drop in the pixel domain. This disparity highlights that **self-attention is particularly critical for compressed-domain inference**.

Because the DCT decorrelates spatial information, purely convolutional operators with local receptive fields struggle to recover global semantic context from sparse frequency maps. MHSA addresses this limitation by enabling direct interactions between distant frequency components, effectively integrating fragmented spectral cues into a coherent representation. The synergy between task-aware spectral pruning and hybrid attention-based modeling is therefore the key factor underlying the superior Pareto efficiency of **TAP-HybridNet**.

VI. Detailed Discussion and Theoretical Perspectives

The empirical results of **TAP-HybridNet** provide deeper insights into machine-centric visual representations and expose fundamental limitations of human-centric compression paradigms when applied to edge vision systems.

A. Information Bottleneck and Semantic Redundancy

The design of **TAP-HybridNet** is firmly grounded in the **Information Bottleneck (IB)** principle [32], which posits that an optimal representation should preserve task-relevant information while discarding irrelevant variability. By explicitly penalizing representation complexity through the $\mathcal{L}_{\text{comp}}$ term, our framework forces the model to converge toward a minimal sufficient statistic for classification.

The learned spectral masks (Fig. 5) reveal a consistent suppression of high-frequency diagonal coefficients. From an information-theoretic perspective, these coefficients exhibit high entropy but low mutual information with respect to semantic class labels. Moreover, they are particularly vulnerable to quantization noise under low bit-rate regimes ($Q < 30$), making them unreliable carriers of semantic content. Discarding such components therefore improves robustness rather than degrading performance.

This behavior aligns closely with recent advances in semantic communication and machine-oriented compression [33], which argue that *Coding for Machines* (CfM) should emphasize structural and relational descriptors over perceptual texture fidelity. Our results empirically validate this hypothesis by demonstrating that aggressive removal of perceptually salient but semantically redundant frequencies can preserve, and in some cases enhance, task performance.

B. Synergy Between TACS and Hybrid Architectures

A central finding of this work is that task-aware spectral pruning alone is insufficient without a backend capable of reasoning over sparse and decorrelated representations. Conventional CNN architectures, such as ResNet-18 [23], rely heavily on local spatial continuity and inductive biases that are poorly matched to the frequency-domain structure induced by the DCT.

When frequency bands are selectively pruned by the **TACS module**, the remaining coefficients form a fragmented and non-uniform representation. The **Multi-Head Self-Attention (MHSA)** layers in **TAP-HybridNet** address this challenge by enabling global interactions across spectral channels and spatial locations [19]. This allows the model to integrate information that would otherwise remain disconnected under purely convolutional processing.

We hypothesize that MHSA effectively acts as a learnable spectral interpolator. Even when intermediate frequency bands are discarded to reduce computation, attention mechanisms can infer semantic relationships by jointly reasoning over low-frequency structural components and residual high-frequency edges. This hypothesis is supported by our ablation results, which show that **TAP-HybridNet** experiences only a 0.45% accuracy drop under aggressive pruning, compared to drops exceeding 1.5% for CNN-only architectures subjected to similar sparsity levels.

C. Pareto Optimality for Edge AI

From a systems perspective, the Rate–Accuracy–Complexity (R-A-C) trade-off achieved by **TAP-HybridNet** represents a meaningful step forward for practical edge deployment. Traditional pipelines require developers to commit to a fixed compression quality factor (Q) and a fixed model architecture at design time, limiting adaptability to dynamic runtime constraints.

In contrast, **TAP-HybridNet** enables flexible resource allocation through task-aware spectral gating. By adjusting the complexity weight λ_C or deploying precomputed spectral masks, the system can dynamically adapt to changing bandwidth, latency, or energy budgets without retraining the backend network. This decoupling of data importance from data format allows the same model to operate across a wide spectrum of deployment scenarios.

Such adaptability is particularly valuable for battery-powered and bandwidth-limited edge devices, where operating conditions can vary unpredictably. By explicitly embedding task awareness into the compressed representation, **TAP-HybridNet** moves beyond static compression-model co-design and toward a more principled, semantics-driven framework for edge AI.

VII. Conclusion and Future Work

In this paper, we introduced **TAP-HybridNet**, a unified framework that synergizes task-aware spectral pruning with an efficient hybrid convolutional architecture. By operating directly in the compressed domain and employing a learnable coefficient selection module, we successfully bypassed the computational bottleneck of JPEG decompression while significantly reducing the dimensionality of the model's input.

Our experimental results on the CIFAR benchmarks demonstrate that **TAP-HybridNet** achieves a **2.9x reduction** in end-to-end latency compared to traditional pixel-domain pipelines, with a negligible loss in accuracy. This efficiency is driven by the multiplicative gains of the **TACS module** frontend and the **HybridConvNet** backbone, which together establish a superior Pareto frontier for Rate-Accuracy-Complexity optimization. Our qualitative analysis confirms that the model naturally learns to prioritize structural low-frequency information, validating the theoretical predictions of machine-centric coding.

Future work will focus on extending the **TAP-HybridNet** framework to video action recognition, where the integration of motion vectors and temporal spectral selection could offer even greater efficiency gains. Additionally, we plan to explore the application of task-aware spectral pruning to dense prediction tasks, such as object detection and semantic segmentation, on high-resolution ImageNet-scale datasets. Ultimately, this work contributes to the realization of truly energy-autonomous edge vision systems capable of real-time intelligence under extreme resource constraints.

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