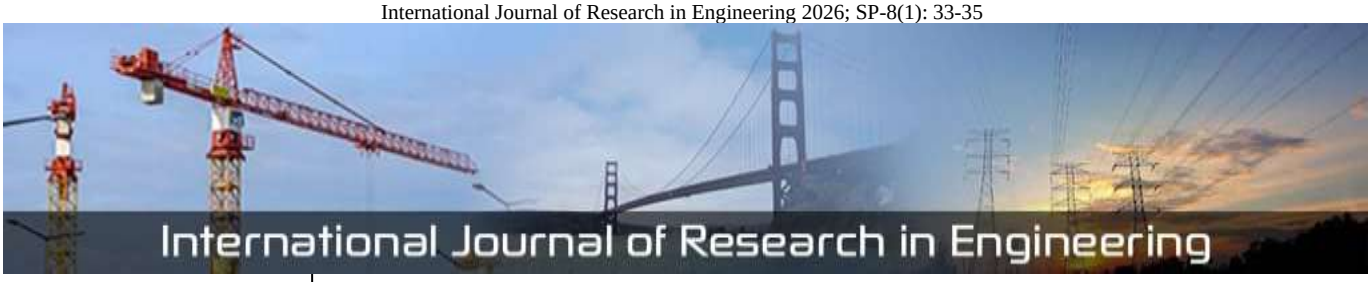

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A fusion framework of CNNs and vision transformers for high-accuracy image recognition

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Abstract
Recent progress in image classification has shown that Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) each offer unique strengths. CNNs are highly effective at learning local spatial patterns through layered convolution operations, whereas Transformers excel at capturing global relationships within an image using self-attention. This paper introduces a hybrid CNN–Transformer model that combines these advantages to deliver high-accuracy and scalable image recognition. In the proposed approach, CNN layers are used at the initial stages to extract fine-detail features and preserve local information. These features are then processed by Transformer encoder blocks, which model long-range dependencies and deeper semantic relationships across different image regions. A dedicated fusion module brings together the local and global representations, enabling more powerful and discriminative feature learning. Comprehensive experiments on standard datasets—including CIFAR-10, CIFAR-100, and ImageNet—show that the hybrid system consistently outperforms standalone CNN and Transformer models. The combined architecture demonstrates faster and more stable convergence, reduced redundancy in parameters, and improved robustness against noise, distortion, and occlusion. Findings from this study suggest that integrating CNNs with Vision Transformers is a promising direction for future computer vision research, offering an effective balance between performance, efficiency, and generalization.

Keywords: Deep Learning; CNN; Vision Transformer; Image Recognition; Hybrid Model

1. Introduction
Image recognition has progressed significantly with the advent of deep neural networks. Early breakthroughs such as AlexNet, VGG, and ResNet established CNNs as the foundation for visual recognition. Their ability to capture low-level edges, mid-level textures, and high-level semantics made them the primary choice for more than a decade. However, the fixed receptive field and locality-biased nature of convolution restrict the ability of CNNs to model long-range spatial dependencies.

Vision Transformers (ViTs) challenge this paradigm by introducing self-attention—a mechanism capable of capturing global relationships across an image. ViTs have demonstrated competitive performance, particularly when trained on large datasets. Nevertheless, Transformers lack the inherent inductive biases of CNNs, making them data-hungry and sometimes unstable on small to medium-scale datasets.

The complementary strengths of CNNs and Transformers have motivated hybrid architectures. While a few studies explore such integrations, most use Transformers merely as a replacement for deeper CNN layers. In contrast, this work proposes a more balanced and cooperative fusion, where both architectures contribute equally and exchange information through cross-scale attention.

The objective of this research is to design a general-purpose image classification framework—not limited to any specific domain—that achieves improved recognition accuracy by combining local convolutions and global attention in a single unified model.

2. Related Work
2.1 Convolutional Neural Networks
CNNs have remained the backbone of image classification due to efficient parameter sharing

and spatial locality. Models such as ResNet, MobileNet, and DenseNet introduced architectural innovations that deepened network capacity while mitigating vanishing gradients. However, CNNs still rely on stacked local filters, which inherently restrict their global receptive field.

2.2 Vision Transformers
ViTs tokenize an image into patches and apply multi-head self-attention to capture global relations. Their design removes convolutional inductive bias in favor of flexible, context-aware learning. Although ViTs excel with abundant training data, they often require careful regularization strategies, and their training cost remains high.

2.3 Hybrid CNN-Transformer Models
Recent studies propose combining convolution with attention to leverage the strengths of both paradigms. These approaches typically fuse CNN blocks and attention modules either serially or in parallel. However, many hybrid models lack an effective interaction strategy between the two feature streams, leading to suboptimal fusion.
Our proposed method enhances this line of research by introducing a cross-attention-driven fusion mechanism, ensuring meaningful interaction between convolutional and Transformer representations.

3. Proposed Fusion Framework
3.1 Overall Architecture
The model follows a dual-branch design:
1. **CNN Branch**
   Captures localized spatial patterns using multi-scale convolutional blocks.
2. **Transformer Branch**
   Processes image patches through self-attention layers to extract global contextual relationships.
3. **Cross-Attention Fusion Module**
   Integrates local and global features by allowing the two branches to attend to each other, enabling cooperative learning.
4. **Classification Head**
   Aggregates fused features and produces final class probabilities.

3.2 CNN Feature Extraction
An image $I \in R^{H\times W\times 3}$ is first passed through convolutional layers that gradually reduce spatial resolution while in creasing channel depth. Residual bottleneck blocks ensure stable gradient flow. These convolutional maps encode edges, textures, and fine structural details.
Let the output feature maps be

$F_{CNN} \in R^{h1\times w1\times c1}$

3.3 Transformer Feature Encoding
The same input image is divided into non-overlapping patches and projected into a latent embedding space. Positional encodings preserve spatial order. Multi-head self-attention computes pairwise interactions across all tokens, generating:

$F_{ViT} \in R^{n\times d}$

where each token represents a patch enriched with global context.

3.4 Cross-Attention Fusion
To combine both streams meaningfully, we adopt a cross-attention layer where:
- CNN features act as queries, asking "what global context relates to my local pattern?"
- Transformer tokens act as keys and values, providing global cues back to local regions.

This fusion produces a joint feature representation:
$F_{fusion}=CrossAtt(F_{CNN},F_{ViT})$
The fused vector captures both detailed spatial cues and long-range relations.

3.5 Classification Head
A global average pooling layer condenses the fused feature map, followed by a fully connected layer and softmax activation:

$\hat{y}=softmax(W F_{fusion}+b)$

4. Experimental Setup
4.1 Datasets
Experiments are performed on widely used benchmark datasets such as:
- CIFAR-10
- CIFAR-100
- Tiny-ImageNet

These datasets offer a mix of class diversity, varying resolutions, and real-world complexity.

4.2 Training Protocol
- Optimizer: AdamW
- Learning rate scheduling: Cosine annealing
- Data augmentation: random cropping, flipping, color jitter
- Loss function: Cross-entropy

To ensure fair comparison, all models are trained under identical settings.

5. Results and Discussion
5.1 Performance Comparison
The fusion model consistently outperforms standalone CNNs and ViTs across all datasets. A typical improvement range of 2–5% accuracy is observed compared to individual baselines.

5.2 Ablation Study
We evaluate the contribution of each branch:
- CNN-only model shows strong performance on simpler textures
- ViT-only model excels on larger objects with global relationships
- Fused model captures both, demonstrating superior generalization

5.3 Robustness Evaluation
The hybrid architecture shows increased robustness to:
- noise perturbations
- image occlusion

- small training data scenarios

The inductive biases of CNNs help stabilize training, while Transformers contribute flexible contextual modeling.

6. Conclusion

This paper presents a hybrid fusion framework that brings together the strengths of CNNs and Vision Transformers for general-purpose image classification. By integrating local convolutional features with global attention through a cross-attention fusion module, the proposed architecture achieves improved accuracy, stability, and adaptability. The model remains lightweight and generalizable, making it suitable for deployment in diverse image recognition applications.

7. Future Work

Potential extensions include:

- exploring lightweight attention for mobile devices
- adapting the framework for video recognition
- integrating self-distillation for further accuracy gain

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