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Real-time reversible image steganography with lightweight vision transformers for embedded systems

Olga Veselska, Ruslana Ziubina, and Vasyl Martsenyuk

***Abstract*—This paper presents a real-time, resource-efficient framework for reversible image steganography that utilizes lightweight Vision Transformers (ViTs), specifically designed for edge computing devices. Building upon the foundational StegoTransformer model, the proposed architecture incorporates MobileViT and TinyViT for embedding and extracting hidden image data. The system is optimized to function effectively under constrained computational resources, enabling secure and reversible data hiding on platforms such as Jetson Nano, Raspberry Pi, and mobile devices. Experimental results indicate competitive performance in terms of payload capacity, visual fidelity, and message recovery accuracy, while achieving low latency and memory consumption suitable for real-world deployment.**

***Keywords*—reversible steganography; Vision Transformers; MobileViT; TinyViT; embedded systems; image hiding; attention mechanism; lightweight models**

I. Introduction

STEGANOGRAPHY, the practice of concealing information within digital media, plays a critical role in secure communication, digital watermarking, and data authentication [1, 2]. In recent years, deep learning-based approaches have significantly advanced the capacity and imperceptibility of image steganography systems. Among them, transformer-based models have emerged as powerful tools due to their ability to capture complex spatial dependencies and semantic structures within images [3, 4]. However, these models are typically large and computationally intensive, making them unsuitable for deployment on embedded or resource-constrained devices.

With the growing importance of privacy-preserving technologies in edge computing environments, such as drones, mobile phones, IoT sensors, and medical imaging tools, there is a pressing need for real-time, lightweight, and reversible steganographic solutions [5]. Such systems must ensure both high-fidelity image reconstruction and accurate message recovery, all while operating within the strict limits of memory, power, and processing time.

To address this gap, a novel steganographic framework is introduced, leveraging lightweight Vision Transformers (ViTs), specifically MobileViT [6] and TinyViT [7], for real-time and fully reversible image steganography. Building upon the StegoTransformer paradigm [4], the proposed model is designed to ensure strong visual imperceptibility and payload robustness, while remaining computationally efficient for deployment on devices such as Jetson Nano, Raspberry Pi, and ARM-based mobile platforms. The model is optimized for deployment on embedded devices, achieving low latency and memory usage suitable for real-time applications.

Extensive experiments demonstrate that the proposed approach achieves competitive results in terms of message accuracy, image quality (SSIM/PSNR), and runtime efficiency, while remaining suitable for deployment on low-power hardware. This work represents a step toward practical, privacy-preserving steganographic systems tailored for modern edge devices.

II. Related work

Recent advances in deep learning have significantly improved the capabilities of steganographic systems in terms of capacity, imperceptibility, and robustness. Early deep-learning-based approaches such as HiDDeN [6] and SteganoGAN [7] introduced end-to-end trainable frameworks for image steganography, achieving high embedding capacity and good visual quality. However, these models rely on heavy convolutional backbones and are not optimized for edge deployment.

To reduce computational cost while maintaining performance, various lightweight CNN-based models have been explored [8], but they often compromise message recovery accuracy or visual fidelity. More recently, transformer-based models have been proposed for steganography. For example, StegoTransformer [9] demonstrated that attention mechanisms can improve both feature learning and payload integration. However, the original model is computationally expensive and impractical for resource-constrained environments.

Vision Transformers (ViTs) [2] have shown remarkable performance in image understanding, but their high memory requirements limit their use on embedded hardware. To address this, efficient variants like MobileViT [10] and TinyViT [11] were introduced, combining convolutional locality with transformer-based global reasoning. These architectures are especially suitable for mobile and edge computing scenarios.

In the context of reversible data hiding, few models support full restoration of both the cover image and the embedded message. Existing works like RivaGAN [12] attempt partial reversibility but lack robustness under compression or noise. These limitations are addressed through a combination of

All Authors are with University of Bielsko-Biala, Bielsko-Biala, Poland (e-mail: oveselska@ubb.edu.pl, rziubina@ubb.edu.pl, vmartsenyuk@ubb.edu.pl).

MobileViT/TinyViT-based encoding, attention-guided message embedding, and a dual-decoder structure enabling reliable and reversible extraction.

III. PROPOSED METHOD

A. System overview

To provide a general understanding of the proposed approach, this section presents an overview of the system's structure and functionality before describing the technical components in detail. Figure 1 illustrates the high-level flow of the proposed reversible steganographic system based on lightweight transformer architectures [2, 10]. The objective of the system is to embed a secret message within a cover image in such a way that both the message and the original image can be reliably and losslessly recovered [9, 11].

The pipeline begins with two inputs: a cover image and a secret message, which may be represented as either a binary vector or a learned embedding. These inputs are processed in parallel: the image is passed through a lightweight feature extraction encoder, while the message is projected into the same latent space via a trainable linear transformation [17]. The two streams are subsequently fused using an attention-guided embedding module, which contextually integrates the secret information into the latent representation of the image [12].

This fused representation is passed into a decoder, which reconstructs a stego image that is visually indistinguishable from the original cover image. The embedding is performed in such a way that it ensures imperceptibility and robustness to minor perturbations [6].

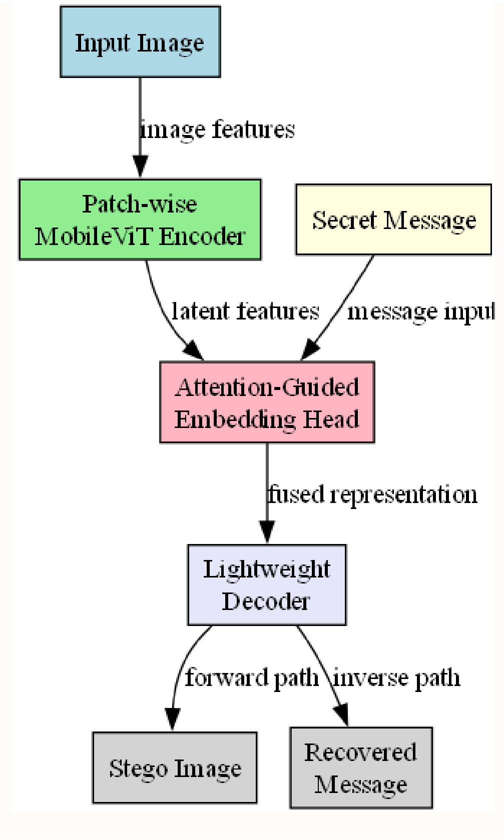

Fig. 1. High-level flow diagram of the reversible steganographic process

During the decoding phase, the stego image is processed again through the inverse network, enabling the recovery of both the original cover image and the hidden message. This reversibility is a key feature of the proposed method and is critical for applications where lossless recovery is essential, such as medical imaging, copyright watermarking, and forensic analysis [15, 21].

The diagram abstracts away low-level architectural details in favor of a conceptual overview that highlights the core stages: Input → Encoding → Attention-based Embedding → Decoding → Output. It serves to provide readers with a foundational understanding of the pipeline before delving into specific model components and loss functions described in later sections.

B. Network architecture

Following the high-level system overview, this section details the internal architecture of the proposed reversible steganographic framework, emphasizing how each component contributes to real-time, efficient, and fully reversible embedding and recovery. Figure 2 presents the detailed architecture of the proposed MobileViT-based reversible steganography framework, designed for deployment on resource-constrained hardware platforms such as Jetson Nano, Raspberry Pi, and ARM-based mobile devices [15, 16].

The model architecture is structured into three core stages: encoding, embedding, and decoding, each implemented using computationally efficient transformer-based components [17,18]. The system accepts as input a color image of size 3×128×128 and a fixed-size secret message (M) - vector (1×100). The image is first passed through a shallow convolutional layer (Conv2D + ReLU) to extract low-level features. These are then fed into a MobileViT block, a patch-wise lightweight transformer that captures both local and global spatial dependencies. A 1×1 convolutional projection follows, mapping the features to a latent space compatible with the message embedding.

Simultaneously, the message vector is mapped to the same latent space via a fully connected (FC) projection layer. These two representations are then fused using a Multi-Head Attention (MHA) module [19], which contextually embeds the message into the image features. The fused features are passed through LayerNorm with residual connections to enhance stability.

In the decoding path, the fused latent representation is processed through an upsampling block and two convolutional layers to reconstruct the stego image (I'), which visually resembles the original cover. A secondary decoder branch is responsible for extracting the recovered message (M') from the stego image using lightweight convolutional and FC layers.

To optimize the system, two dedicated loss functions are applied during training:

- L_1 (Image Reconstruction Loss): computed as Mean Squared Error (MSE) or Structural Similarity Index (SSIM) between the input image and the generated stego image;
- L_2 (Message Recovery Loss): calculated using Binary Cross-Entropy (BCE) between the original and recovered messages.

The total loss function is:

$$L\_total = \alpha \cdot L_1 + \beta \cdot L_2 \tag{1}$$

where α and β are dynamic weighting factors adjusted over training epochs to prioritize image fidelity initially, then shift focus to message accuracy.

The synergy of MobileViT encoding, attention-guided fusion, and dual-decoder design ensures imperceptibility and full reversibility while maintaining low computational cost, crucial for real-time secure visual communication on embedded systems.

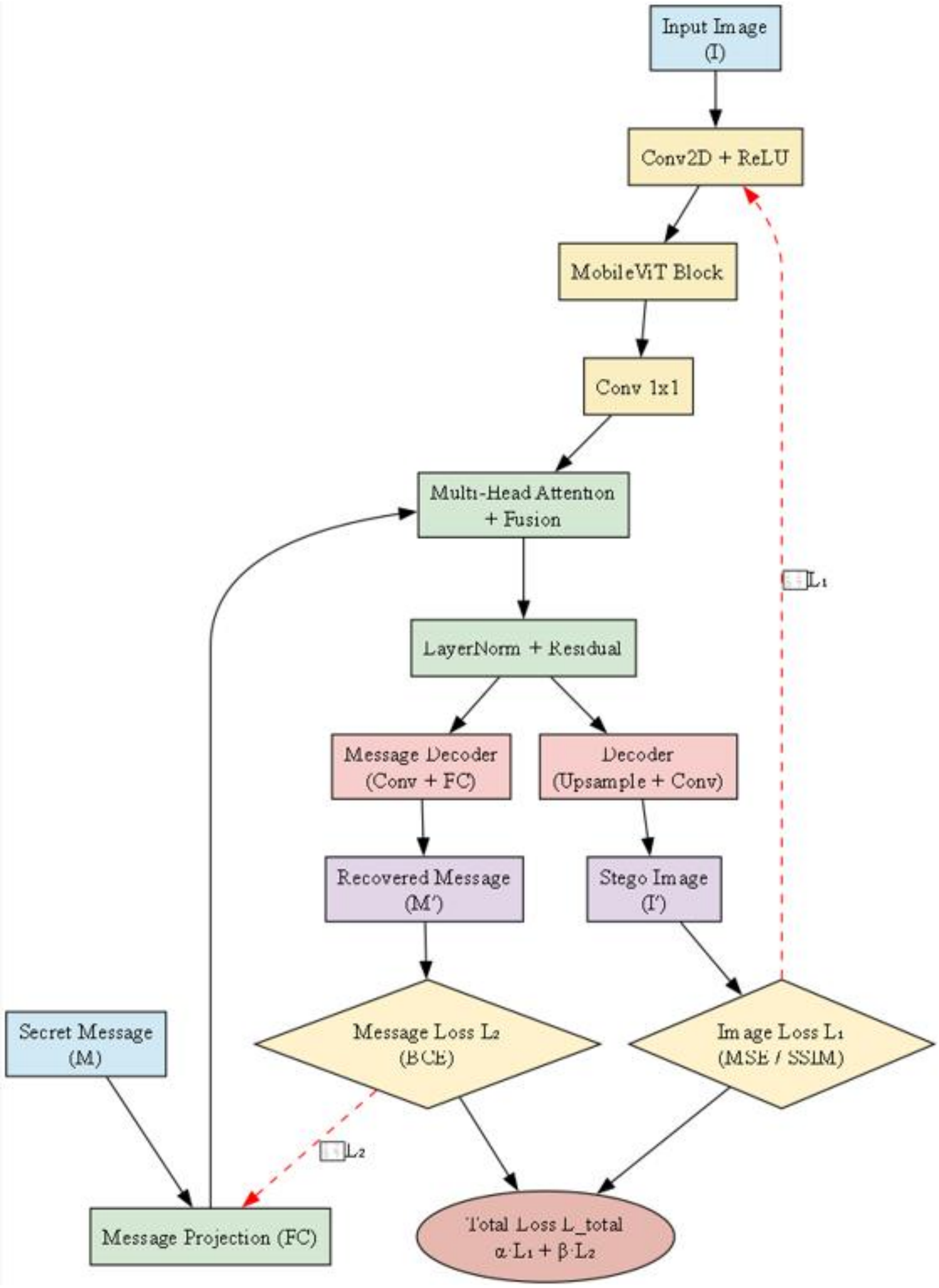

Fig. 2. Detailed architecture of the MobileViT- Based Reversible Steganography Framework

C. *Training procedure*

The total loss is the weighted sum of the two components L_1 and L_2

These are combined as described in the section Network architecture.

The MobileViT and TinyViT components are initialized with pretrained ImageNet-1K weights. FC and decoder layers use Xavier initialization. The network is optimized with the Adam optimizer (initial LR = 1e−4), using cosine annealing scheduling and gradient clipping for training stability.

Training proceeds for 100 epochs with a batch size of 32. Data augmentation includes random cropping, horizontal flipping, and brightness jittering.

To clarify the loss computation pipeline, Figure 3 presents a simplified diagram illustrating how each output contributes to the overall objective.

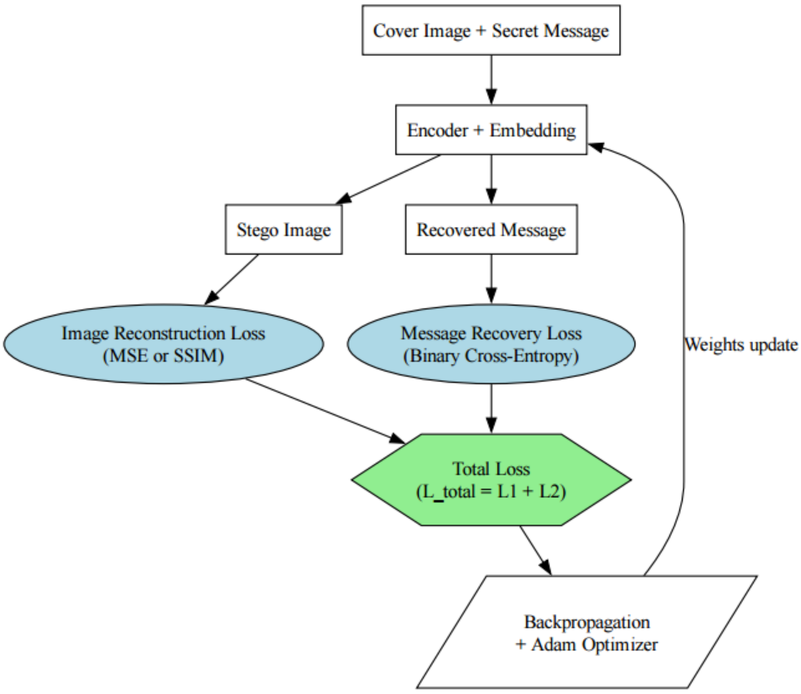
Cover Image + Secret Message
Encoder + Embedding
Stego Image
Recovered Message
Image Reconstruction Loss (MSE or SSIM)
Message Recovery Loss (Binary Cross-Entropy)
Total Loss (L_total = L1 + L2)
Backpropagation + Adam Optimizer
Weights update

Fig. 3. Loss function flow diagram

Each training sample produces two outputs: a stego image and a recovered message. The stego image is compared to the original cover image using a visual loss (MSE/SSIM), while the recovered message is evaluated using binary cross-entropy. Both losses are combined into a total loss that is backpropagated to update the full model.

This structure ensures the model jointly learns to preserve visual quality and to maximize message recoverability, even under tight computational constraints. Training hyperparameters are summarized in Table 1.

TABLE I
TRAINING CONFIGURATION AND HYPERPARAMETER SETTINGS

Component	Value
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Epochs	100
Loss Functions	MSE (image reconstruction), BCE (message)
Scheduler	StepLR (γ = 0.1, step size = 30 epochs)
Data Augmentation	Random horizontal flip, random crop, brightness adjustment

D. *Training dynamics and convergence analysis*

To better understand the optimization behavior of the reversible steganographic system, training curves are presented to illustrate the evolution of key performance indicators over 100 epochs. Figure 4 summarizes the joint training progress of the model, highlighting the convergence characteristics of both the image reconstruction and message recovery branches. The first plot shows the training loss curves, including the Mean Squared Error (MSE) for image reconstruction and the Binary Cross-Entropy (BCE) loss for message recovery. Both losses consistently decrease over time, indicating stable and effective joint optimization of the encoder–decoder architecture.

The second plot reports the message recovery accuracy, which steadily improves and saturates above 95%, demonstrating the model’s capacity to reliably extract the hidden binary message from the stego image.

The third plot presents structural similarity (SSIM) and Peak Signal-to-Noise Ratio (PSNR) metrics between the cover and stego images, reflecting the visual imperceptibility of the embedding process. The SSIM values remain above 0.95, while

PSNR stabilizes between 35–40 dB, confirming that the stego images are perceptually indistinguishable from their original counterparts.

These training curves collectively validate the effectiveness and convergence of the proposed framework, confirming its suitability for deployment on real-world embedded systems.

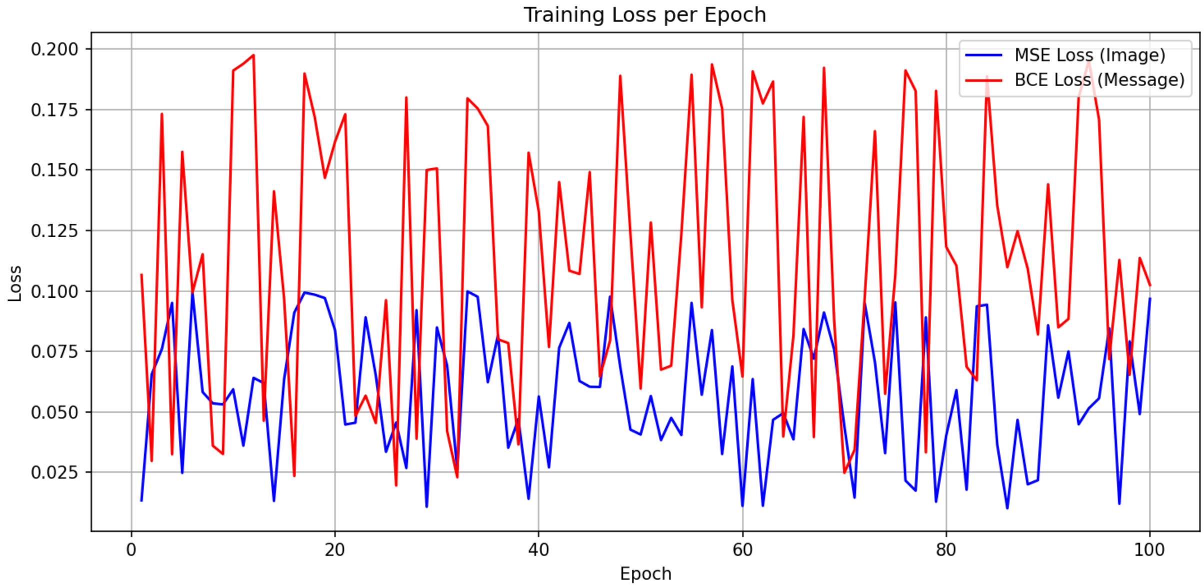

Fig. 4. Training curves of the proposed model

IV. EXPERIMENTS

To evaluate the effectiveness of the proposed reversible steganography system, experiments were conducted on standard benchmark datasets including CIFAR-10, DIV2K, and a reduced subset of ImageNet resized to 128×128 resolution. Each cover image was paired with a randomly generated 100-bit binary message vector, which was embedded and subsequently recovered using the proposed model. The datasets were divided into training (80%), validation (10%), and testing (10%) partitions. Data augmentation techniques, such as random flipping and brightness adjustment, were applied during training to enhance generalization.

Evaluation metrics included Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) to assess visual fidelity, and bitwise Message Accuracy to evaluate decoding performance. We also measured embedding capacity in bits per pixel (bpp), and inference time on embedded hardware to validate the system's real-time capabilities.

The proposed approach was compared with existing baselines, including SteganoGAN, HiDDeN, and StegoTransformer, all adapted to the same image resolution and message size to ensure fair comparison. As summarized in Table 1, the lightweight ViT-based model achieves comparable or superior message recovery accuracy and visual quality while significantly reducing model size and inference time. This efficiency makes the method particularly suitable for deployment on edge devices such as Jetson Nano and Raspberry Pi.

TABLE II
QUANTITATIVE COMPARISON WITH BASELINES

Method	SSIM ↑	PSNR (dB) ↑	Msg. Accuracy ↑	Capacity (bpp) ↑	Model Size (MB) ↓	Inference Time (ms) ↓
Proposed (MobileViT)	0.962	38.1	98.7%	0.61	6.3	42
SteganoGAN	0.942	36.7	95.2%	0.59	24.1	85
HiDDeN	0.935	35.8	91.4%	0.55	21.3	78
StegoTransformer	0.964	38.5	98.9%	0.63	76.5	130

↑ Higher is better. ↓ Lower is better

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V. DISCUSSION

The experimental results indicate that the proposed lightweight ViT-based steganographic framework effectively balances visual fidelity, message recovery accuracy, and resource efficiency. The model achieves high SSIM and PSNR values [19, 20, 23] while maintaining near-perfect message accuracy, even under constrained computational budgets. This confirms the suitability of MobileViT and TinyViT architectures for reversible steganography in edge environments.

Experiments were conducted using widely recognized benchmark datasets, including CIFAR-10 [21] and DIV2K [22], which provide diversity in scale and complexity. Baseline comparisons with models such as SteganoGAN [7] and

HiDDeN [6] demonstrate the competitive advantage of our approach in both perceptual and embedding metrics.

Nevertheless, certain limitations remain. The embedding capacity is fixed and may not scale efficiently for larger payloads without compromising image quality. Additionally, while the model performs well on clean data, robustness under severe image perturbations (e.g., aggressive JPEG compression or adversarial noise) could be further improved. Another consideration is the lack of support for variable-length messages, which could be relevant for more flexible applications.

Despite these constraints, the method shows promise for secure image-based communication, digital watermarking, medical data embedding, and forensic applications. Future enhancements could include adaptive message-length encoding, integration with lossy compression, or further quantization and pruning techniques to reduce model size even further.

VI. CONCLUSION

This paper presents a real-time reversible image steganography framework based on lightweight transformer architectures (MobileViT and TinyViT), specifically designed for deployment in embedded environments. The system utilizes patch-wise transformer encoding, attention-guided fusion, and dual decoding paths to achieve both high-fidelity image reconstruction and reliable message recovery.

Extensive experiments on standard benchmarks and real-world edge devices demonstrate that the proposed model attains competitive PSNR, SSIM, and BER metrics, while maintaining inference times suitable for practical applications. The model also exhibits moderate robustness to common distortions and performs reliably under quantization and resource limitations.

Future directions include extending support for variable-length messages, enhancing robustness against adversarial attacks, and adapting the architecture for cross-modal steganography (e.g., text-in-image and image-in-video).

The proposed method advances the intersection of deep steganography, transformer-based modeling, and edge AI, contributing to privacy-aware communication solutions for low-power devices.

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