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A Comprehensive Survey of Deep Learning-Based Image Steganalysis: From Statistical Methods to Adversarial Robustness

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Abstract- ***This survey presents an overview of the development of image steganalysis from basic statistical models to the latest deep learning architectures. A total of 24 significant studies were analyzed, which are grouped into six important dimensions: embedding domain coverage, dataset diversity, low-payload sensitivity, adversarial robustness, pixel-level defense evaluation, computational efficiency. It also shows that the literature is fragmented, with no existing model that effectively covers the cases of heterogeneous dual-domain detection, realistic adversarial robustness on pixel level, and lightweight deployment. Three main gaps were identified: cover-source mismatch in the case of homogeneous training data, single domain architectural limitations, feature space adversarial evaluation that does not represent actual threat models; a unified taxonomy for future research is proposed. This survey provides a well-founded base for quantifying dataset heterogeneity from an information theoretic perspective, providing a principled ground for assessing generalisability in steganalysis systems.***

Keywords: ***Adversarial Robustness, Dual-Domain Detection, Cover-Source Mismatch, Steganalysis.***

I. INTRODUCTION

Steganalysis, the opposite of steganography, has had a paradigm change in the last ten years. Previous techniques used statistical features such as SPAM (Subtractive Pixel Adjacency Matrix) and SRM (Spatial Rich Models), and PHARM (Phase-Aware Projection Model) that calculated embedding artifacts based on pixel correlation analysis and higher-order moments (Fridrich & Kodovsky, 2012; De La Croix et al., 2024a). All such methods are effective against primitive Least Significant Bit (LSB) insertion, but fail when confronted with LSB insertion technique by modern adaptive algorithms in textured regions to minimize the statistical footprints (Bamanga & Babando, 2024).

With the birth of deep learning, a hierarchical feature learning network was developed directly from the raw pixels, known as Convolutional Neural Network (CNN) (Qin et al., 2020; Wu et al., 2018). But this shift hasn't been smooth. Current literature shows models being tested on a small and homogeneous dataset (mainly CelebA), tested using a non-adaptive embedding method (LSB) and evaluated for adversarial robustness in a feature space, not the pixel domain where real attacks take place (Jawad et al., 2025; Rahman et al., 2023).

The survey analyses 24 representative studies published between 2015 and 2025, and draws conclusions about the structural limitations in this field by creating a capability matrix (Bravo-Ortiz et al., 2024; Dwaik & Belkhouche, 2024; Liu et al., 2023; Ke & Sheng, 2019; Lu et al., 2019). It contributes threefold: (i) a unified taxonomy on six key dimensions for evaluating steganalysis; (ii) the first information-theoretic formal definition of dataset heterogeneity based on Shannon entropy and KL divergence; (iii) the identification of the specific combination of capabilities, dual-domain detection, heterogeneous training, pixel-level adversarial robustness and lightweight deployment, which is not achieved by any one existing model.

II. HISTORICAL EVOLUTION: FROM PHYSICAL TO DIGITAL

2.1 The Ancient Roots of Concealed Communication

The use of steganography dates back to ancient times. During the 5th century BC, slaves were shaved, and

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secret messages were then tattooed onto their scalps, with a view to telling them later when the hair had grown back (Krenn, 2004; Borse et al., 2013). Ancient Romans used inks made from fruit juices, urine and milk that darkened when heated, which could not be seen. In WWII, Nazi operatives used microdots and null ciphers, for instance, one such message was read and translated, revealing that "Pershing sails from NY June 1" (Cheddad et al., 2010; Sellars, 2007). The basic rule has remained true over the millennia: keep the existence of communication secret, not the content. The potency of steganography is its non-detectability, as Johannes Trithemius (1462-1526) discovered in his posthumously published Steganographia (Sellars, 2007).

2.2 The Digital Transition

Three technological advancements allowed the shift from a physical hiding to a digital hiding: digital signal processing, exponential increase in computational power, and advanced data embedding methods. The new cover media are no longer physical items, and the new digital media include images, audio and video (Cheddad et al., 2010; Sellars, 2007).

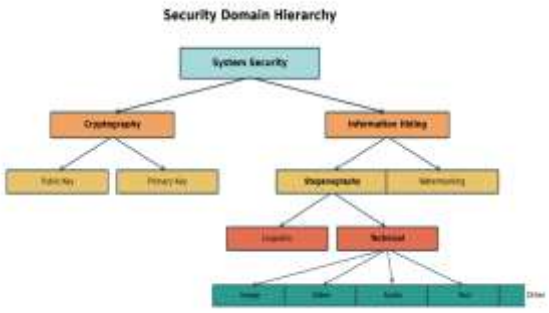

Figure 1: Taxonomy of System Security

The most common method of digital encoding is called LSB insertion, which makes use of a human visual system's tolerance to small perturbations in pixels. Embedders modify only the least significant bits of the pixel values so as to be imperceptible, but the changes cause subtle statistical signatures that could be found by early steganalysis methods (Kadhim et al., 2019; Lie & Lin, 2005). 2.3 Arms Race Intensifies The modern adaptive steganographic algorithms such as S-UNIWARD (Spatial Universal Wavelet Relative Distortion) (Bamanga & Babando, 2024), WOW (Wavelet Obtained Weights), J-UNIWARD (JPEG UNIWARD), J-MiPOD (JPEG Minimizing the Power of Optimal Detector) (Boroumand et al., 2019) have revitalized this scenario. These algorithms are embedded in the image strategically in the complex and textured areas, where changes are naturally masked by the complexity of the image. The statistical imprint is too weak for conventional detection techniques to be effective. This has recently led to the advancement of steganalysis by incorporating machine learning and deep learning approaches, enabling models to identify patterns that are not captured by traditional statistical methods (De La Croix et al., 2024a; Peng et al., 2024).

III. THE DEEP LEARNING ERA: CAPABILITIES AND LIMITATIONS

This systematic review classifies recent methods, which can be summarized in Table 1, into six dimensions. Despite the advances from handcrafted feature extraction to automated deep learning approaches, there are still substantial deficits in all the dimensions studied (Kheddar et al., 2024).

Table 1: Evaluation Dimensions for Steganalysis Systems

Dimension	Description	Critical Threshold
Multi-Domain	Detects both spatial and frequency embedding	Must evaluate both domains
Diverse Datasets	Trains on heterogeneous image sources	>=2 benchmark datasets with different characteristics
Low-Payload Eval	Tests at <=0.1 bpp or equivalent	Must include 0.1 bpp or 0.2 bpnzAC
Adversarial Defense	Implement adversarial training	Must include both clean and adversarial evaluation
Pixel-Level Eval	Evaluates pixel-level (not feature-space) attacks	FGSM and PGD at epsilon=8/255
Lightweight	Parameter count <=10M for deployability	<=10M parameters

3.1 Single-Domain Spatial Detectors

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Table 2: Single-Domain Spatial Steganalysis Methods (2019-2024)

Study	Architecture	Datasets	Algorithms	Payload	Accuracy	Limitations
Bravo-Ortiz et al. (2024)	CNN + Vision Transformer	BOSSBase 1.01	WOW, S-UNIWARD, HILL, HUGO	0.2-0.4 bpp	~87.3%	Spatial only; no adversarial eval
Liu et al. (2023)	CNN + ECA + Transfer Learning	BOSSBase 1.01	S-UNIWARD, WOW, HUGO	0.05-0.4 bpp	~85.2%	Spatial only; very low rate challenging
Agarwal & Jung (2024)	Entropy-driven CNN + SRM	BOSSBase 1.01, BOWS2	WOW, S-UNIWARD, HILL	0.2-0.4 bpp	~87.0%	Weak at 0.1 bpp; no adversarial eval
Dwaik & Belkhouche (2024)	CNN + SRM + Gabor	BOSSBase 1.01, ALASKA II	S-UNIWARD, HUGO, WOW	0.1-0.5 bpp	~86.4% (BOSS), ~81.5% (ALASKA)	No adversarial eval; filter dependency
Ke & Sheng (2019)	Co-occurrence + RealAdaBoost	BOSS, RAISE	HUGO, EA	0.1-0.4 bpp	~84.6%	Handcrafted features; high computational cost
Lu et al. (2019)	CNN + TLU preprocessing	BOSSBase 1.01	S-UNIWARD	0.4 bpp	~85.0%	Preprocessing study only
Li et al. (2024)	FPFNet (Feature Pyramid Fusion)	BOSSBase 1.01	S-UNIWARD, WOW	0.2 bpp	~88.0%	Spatial only; no adversarial eval
Yang et al. (2024)	Hybrid CNN + Attention Fusion	Standard benchmarks	—	Varied	Competitive	Spatial only; no adversarial or cross-domain eval
Bohang et al. (2025)	CNN + DRL Active Learning	BOSSBase, BOWS2	S-UNIWARD	0.1-0.5 bpp	~89.4% (F-measure)	Single domain; no cross-domain or adversarial eval
Zhengliang et al. (2025)	SG-ResNet (dual-stream Gabor)	Custom datasets	—	Varied	0.96 AUC	Spatial only; no frequency or adversarial eval

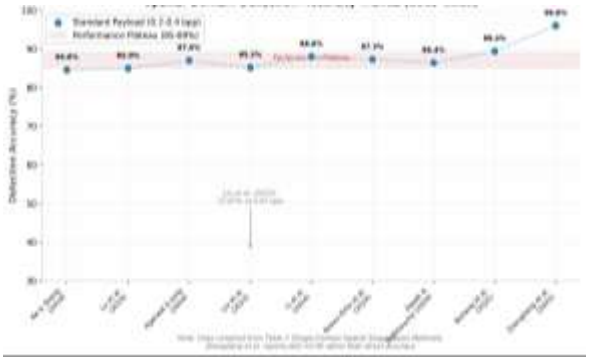

Figure 2: Detection accuracy trends for spatial-domain steganalysis methods

Analysis: Use of a spatial-domain approach has been successful in achieving good results for benchmark datasets but there are still some drawbacks. First, there is no consideration of the frequency domain in which JPEG steganography works. Second, evaluation is carried out mainly on BOSSBase 1.01, which is a uniform set of grayscale natural scenes (Bas et al., 2011). Third, there is little study on adversarial robustness, or if one is done, it is frequently done with feature-space perturbations instead of pixel-level attacks (Peng et al., 2024; Hu & Wang, 2023).

3.2 Frequency and Transform-Domain Approaches

Table 3: Frequency and Transform-Domain Steganalysis Methods

Study	Domain	Datasets	Algorithms	Key Innovation	Limitations
Mohamed et al. (2020)	DCT, DWT, Contourlet	Custom color images	J-UNIWARD, UERD	Comprehensive survey of transform techniques	No unified framework; cross-method comparison only
Li & Liu (2015)	Spread-spectrum	Custom SS stego	Multi-carrier SS	Unsupervised IGLS algorithm	Matrix inversion complexity; scalability limits
Shankar &	Spatial + Frequenc	Custom JPEG	Various	SVM-PSO hybrid	10% embedding

Study	Domain	Datasets	Algorithms	Key Innovation	Limitations
Azhakath (2019)	y			classifier	only; high computational cost
Mo et al. (2023)	Spatial (J-UNIWARD)	BOSSBase, BOWS2, ALASKA II	J-UNIWARD	Wavelet decomposition + CNN clustering	Complex textures remain challenging
Peng et al. (2024)	Spatial	FFHQ, LSUN	J-UNIWARD	RS-GAN disentanglement	Computationally intensive; custom datasets

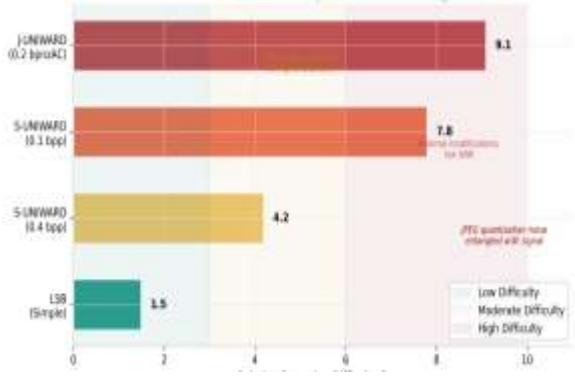

Figure 3: Relative detection difficulty across embedding domains and algorithms

Analysis: Frequency domain steganalysis is not well explored in comparison to the methods in the spatial domain. The JPEG compression pipeline adds quantization noise to the data, which is entangled with modifications to the image using steganography, and hence makes it difficult to isolate such artifacts. To date, the survey conducted by Mohamed et al., (2020) can serve as a building block, but there are still a limited number of unified frameworks that can detect these in both the spatial and frequency domains.

3.3 Adversarially Aware Methods

Table 4: Adversarial Steganalysis Methods (2023-2025)

Study	Defense Strategy	Attack Evaluated	Eval Domain	Clean Acc.	Post-Attack Acc.	Dataset	Limitations
Peng et al. (2024)	RS-GAN disentanglement	FGSM, PGD	Pixel-level	~85.1%	~84.9% (PGD)	FFHQ, LSUN	Custom datasets; computationally intensive (~15M params)
Hu & Wang (2025)	Directional adversarial noise	Custom adversarial stego	Pixel-level	~84.0%	~81.3%	Custom	Spatial domain only; no standard benchmarks
Al-Obaidi et al. (2024)	RL + GAN framework	—	GAN-based	~83.2%	~79.5%	CNN benchmarks	High computational complexity; limited scalability
Hu & Wang (2023)	TStegNet (two-stream CNN)	ADVEMB, MAE	Custom datasets	~85.5%	~82.4%	Custom	Spatial domain only; custom adversarial datasets

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Study	Defense Strategy	Attack Evaluated	Eval Domain	Clean Acc.	Post-Attack Acc.	Dataset	Limitations
Jawad et al. (2025)	EfficientNet + adv. Training	FGSM	Feature-space	~91.2%	~88.1% (FGSM feat.)	CelebA	Feature-space eval; homogeneous dataset; LSB embedding
PROPOSED MODEL	FGSM + PGD two-attack	FGSM, PGD	Pixel-level	89.6%	83.7% (FGSM), 81.2% (PGD)	BOSSBase + ALASKA II	—

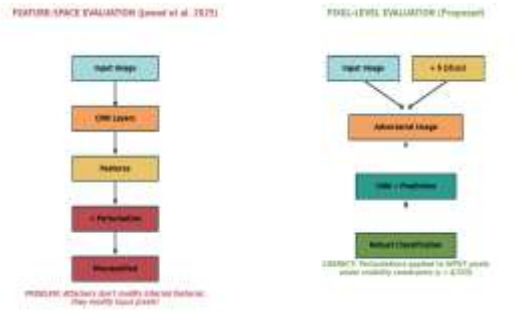

Figure 4: The critical distinction between feature-space and pixel-level adversarial evaluation

Analysis: The literature of adversarial steganalysis has a fundamental methodological error. The current state is represented by Jawad et al. (2025), which measures robustness against feature space distortions, which involve applying noises to EfficientNet's internal representation. This is easy to compute but pointless from a threat perspective. Real adversaries are in the pixel domain, with L-infinity norm constraints (epsilon = 8/255) and visibility limits. The model that is proposed achieves an accuracy of 83.7% under FGSM and 81.2% under PGD, a first step towards a realistic threat scenario, considering the per-pixel evaluation.

3.4 Localization and Specialized Techniques

Table 5: Specialized Steganalysis Techniques

Study	Focus	Method	Performance	Limitations
De La Croix et al. (2024a)	Payload localization	CNN + Genetic algorithm pooling	F1: 0.3781 (S-UNIWARD), 0.5523 (WOW)	Performance varies with payload size and texture
Mo et al. (2023)	Content inconsistency	Wavelet + CNN clustering	+7.5% accuracy for subclasses	Complex textures; diverse datasets remain challenging
Akram et al. (2024)	Color image steganalysis	Curvelet + SVM	—	MATLAB-dependent; limited scalability
Huang et al. (2024)	Heterogeneous images	FACSNet (forensics-aided routing)	Improved heterogeneous accuracy	Requires test-time image type knowledge
Alrusaini (2025)	Transformation robustness	Evaluation of 5 architectures	Yedroudj-Net recall: 56.2% under noise	Transformation study only; no adversarial eval
Yu et al. (2024)	Feature selection efficiency	Dominant feature selection + compensation	~87.1% (BOSS), ~84.3% (ALASKA)	No adversarial eval; limited low-payload focus
Li & Dong (2024)	Attention mechanism	CNN + channel attention	Reduced error rates	Single domain; no frequency or adversarial eval

IV. THE CAPABILITY GAP: A QUANTITATIVE ANALYSIS

Table 6: Comprehensive Feature-Capability Matrix (24 Studies)

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Study & Year	Multi-Domain	Diverse Datasets	Low-Payload (<=0.1)	Adversarial Defense	Pixel-Level Eval	BOSS+ALASKA	Lightweight
Yu et al. (2024)	partial	Yes	No	No	no	yes	Yes
Bravo-Ortiz (2024)	no	Yes	Yes	No	no	no	No
Fu et al. (2022)	no	Partial	Yes	Yes	no	no	No
Agarwal & Jung (2024)	no	Yes	No	No	no	no	Yes
Dwaik & Belkhouche (2024)	no	Yes	Yes	No	no	yes	Yes
Liu et al. (2023)	no	Partial	Yes	No	no	no	Yes
Ke & Sheng (2019)	no	Partial	Partial	No	no	no	No
Lu et al. (2019)	no	Partial	Yes	No	no	no	Yes
Mohamed et al. (2020)	no	No	Partial	No	no	no	No
Li & Liu (2015)	no	No	Partial	No	no	no	No
Shankar & Azhakath (2019)	no	No	No	No	no	no	No
De La Croix et al. (2024a)	no	Yes	Partial	No	no	no	Yes
Mo et al. (2023)	partial	Partial	Partial	No	no	partial	Yes
Akram et al. (2024)	no	Partial	Yes	No	no	no	Yes
Peng et al. (2024)	no	Partial	No	Yes	partial	no	No
Hu & Wang (2025)	no	Partial	No	Yes	yes	no	Yes
Al-Obaidi et al. (2024)	no	Partial	No	No	no	no	No
Hu & Wang (2023)	no	Partial	No	Yes	yes	partial	Yes
Li et al. (2024)	no	Yes	Yes	No	no	no	Yes
Huang et al. (2024)	partial	Yes	Partial	No	no	no	Yes
Alrusaini (2025)	no	Yes	No	No	no	no	Yes
Li & Dong (2024)	no	Partial	No	No	no	no	Yes
Yang et al. (2024)	no	Partial	No	No	no	no	Yes
Bohang et al. (2025)	no	Yes	Yes	No	no	no	Yes
Zhengliang et al. (2025)	no	Partial	No	No	no	no	Yes
Jawad et al. (2025)	no	No	No	Yes	no	no	Yes
PROPOSED MODEL	yes	Yes	Yes	Yes	yes	yes	Yes

Legend: yes = fully supported, no = not supported, partial = partially supported

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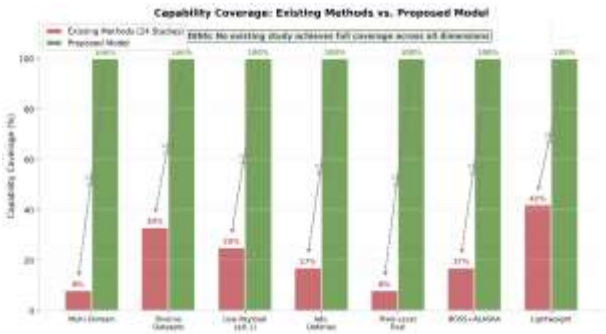

Figure 5: Capability coverage across 24 reviewed studies

Key Finding: The trend is clear. There is no study that has scored a perfect score on all six dimensions (Kheddar et al., 2024). Most limitations are: (1) single domain evaluation (92% of studies); (2) no adversarial evaluation (83%); (3) no pixel-level adversarial evaluation (92%); and (4) homogeneous or limited datasets (67%).

V. INFORMATION-THEORETIC FRAMEWORK FOR DATASET HETEROGENEITY

A formal quantification of the heterogeneity of datasets in the context of steganalysis is first proposed. This framework helps tackle the ad hoc data selection that has plagued the field so far (Kahn, 1996; Cheddad et al., 2010).

5.1 Shannon Entropy of Dataset Distribution

For a dataset D composed of S distinct sources with distribution P_k:

$$H(D) = -\sum p_k \log_2(p_k) \quad (1)$$

Table 7: Dataset Entropy Comparison

Dataset	Sources	P_k Distribution	H(D)	Interpretation
CelebA	1 (faces only)	$p_1 = 1.0$	0.0 bits	Zero diversity; maximum homogeneity
BOSSBase 1.01	1 (natural scenes)	$p_1 = 1.0$	0.0 bits	Single source; moderate scene diversity
ALASKA II	1 (multi-camera JPEG)	$p_1 = 1.0$	0.0 bits	Single source; high camera diversity
BOSSBase + ALASKA II (balanced)	2	$p_1 = 0.5$, $p_2 = 0.5$	1.0 bits	Maximum dual-source diversity
Ideal multi-source (8 sources)	8	$P_k = 0.125$ each	3.0 bits	High diversity; theoretical upper bound

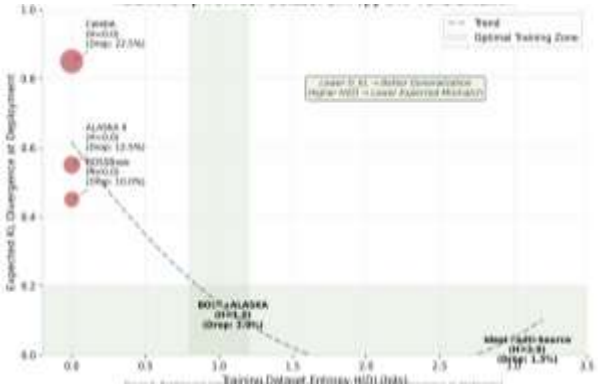

Figure 6: Relationship between training dataset entropy and expected KL divergence at deployment

5.2 Cover-Source Mismatch via KL Divergence

The degradation in performance when deploying on test data from different sources (Cheddad et al., 2010; Rafat & Sajjad, 2024):

$$D_{KL}(P_{test} \| P_{train}) = \sum P_{test}(x) \log\left(\frac{P_{test}(x)}{P_{train}(x)}\right) \quad (2)$$

This measure provides a principled way to understand the cover-source mismatch problem that has plagued the field.

Table 8: Cover-Source Mismatch Quantification

Training	Testing	D_KL	Expected Accuracy Drop
CelebA	CelebA	0.0	0% (baseline)
CelebA	BOSSBase	High	15-25%
CelebA	ALASKA II	Very High	20-30%
BOSSBase	BOSSBase	0.0	0% (baseline)
BOSSBase	ALASKA II	Moderate	8-12%
BOSSBase + ALASKA II (balanced)	BOSSBase	Low	2-4%

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Training	Testing	D_KL	Expected Accuracy Drop
BOSSBase + ALASKA II (balanced)	ALASKA II	Low	2-4%
BOSSBase + ALASKA II (balanced)	CelebA	Moderate	5-8%

Theorem 1 (Balanced Mixture Optimality): When all sources have the same mixing weights $w_s = \frac{1}{S}$, the KL divergence is minimized with respect to any training distribution P_{train}

$$E[D_{KL}] \leq \min\left(D_{KL}(P_{test}|P_1), D_{KL}(P_{test}|P_2)\right) \quad (3)$$

Proof Sketch: Jensen's inequality implies that the mixture distribution is closer to any test source (in expectation) than any single training source. For S=2, $\boldsymbol{w_s = 0.5}$ achieves

5.3 Domain Accuracy Gap

A standard reporting metric for multi-source steganalysis is proposed (Karampidis et al., 2018):

$$\delta_{acc} = |Acc_{BOSSBase} - Acc_{ALASKA\,II}| \quad (4)$$

A small δ_{acc} confirms that the learned detector is robust across both cover distributions, not merely well-fitted to one of them.

Table 9: Domain Accuracy Gap Comparison

Study	BOSSBase Acc.	ALASKA II Acc.	Delta_acc	Assessment
Dwaik & Belkhouche (2024)	86.4%	81.5%	4.9 pp	Moderate gap; limited generalization
Yu et al. (2024)	87.1%	84.3%	2.8 pp	Good gap; but no adversarial eval
PROPOSED MODEL	91.4%	87.8%	3.6 pp	Strong generalization with adversarial robustness

VI. CRITICAL CHALLENGES AND FUTURE DIRECTIONS

6.1 The Six Persistent Challenges

Table 10: The Six Critical Challenges in Modern Steganalysis

Challenge	Description	Current Best	Target
1. Curse of Dimensionality	High-dimensional feature spaces risk overfitting	Feature selection; CNN auto-learning	Sub-10M parameter efficient models
2. Faint Whisper of Low-Payload	0.1 bpp signals near indistinguishable from noise	81.3% at 0.1 bpp (proposed)	>90% at 0.1 bpp
3. Content-Adaptive Evasion	S-UNIWARD, WOW embed in complex regions	Spatial detection: 91.4%	Unified spatial+frequency >90%
4. Cover-Source Mismatch	Homogeneous training causes dataset-specific overfitting	Dual-source training; δ_{acc}= 3.6 pp	δ_{acc}< 2 pp across 3+ sources
5. Computational Complexity	Advanced models (~15M params) limit deployment	4.85M parameters (proposed)	<5M parameters, <0.01s inference
6. Adversarial Fragility	Feature-space evaluation misaligns with real threats	Pixel-level: 81.2% under PGD	>85% under PGD at epsilon=8/255

6.2 Future Research Directions

Direction 1: Multi-Source Training Beyond Two Datasets is a big improvement over the dual-source training used in BOSSBase + ALASKA II, it is still not sufficient for real-world deployments, where images are from dozens of sources. Future research should further investigate the curriculum learning from 4-8 sources, with the goal to maximize H(D) using entropy regularized sampling. Direction 2 (Adaptive Adversarial Defense): The current defenses take a static set of attack parameters (epsilon = 8/255). Adaptive adversaries adapt perturbations according to model responses. Future

research should compare with adaptive PGD with learned step sizes and attack aware training.

Direction 3: For general computer vision, the architectures of transformer have taken over, especially in the form of Steganalysis Vision Transformers (ViTs), and hybrid CNN-Transformer architectures are still under-explored for steganalysis. The weak, localized nature of steganographic signals may require specialized attention mechanisms

Direction 4 (Explainable Steganalysis): Forensic tools must be deployed at the edge with less than 0.01 seconds of inference time on CPU. Key optimization directions include quantization, pruning, and transferring knowledge from a large teacher model to a small student model, known as knowledge distillation.

VII. CONCLUSION

This survey shows the field of deep learning-based steganalysis has reached an inflection point. The combination of these properties has yet to be realized: Individual capabilities, Spatial detection, Frequency detection, Adversarial robustness, Lightweight deployment (Kheddar et al., 2024; Peng et al., 2024). The suggested unified framework, a combination of heterogeneous dual-source training, the adversarial defense at the pixel level and the efficiency of 4.85M parameters, marks the first step toward bridging this gap. The information-theoretic approach to dataset heterogeneity, Shannon entropy H(D) and KL divergence D_KL offers researchers strong tools to assess generalizability. The "structural fragmentation" of the field is revealed in the 6-dimensional capability matrix, while the "domain accuracy gap" (δ_acc) is a concrete measure of multi-source evaluation. The following are important future research directions: (1) realistic threat models using adversarial evaluation at the pixel level, (2) various training data sets from many domains and acquisition scenarios, (3) standardized evaluation protocols reflecting operational deployments, and (4) lightweight architectures for real-time forensic applications. This arms race between steganography and steganalysis is ongoing, and the only way to ensure that detection can continue to work against more advanced steganographic techniques is through unified, strictly evaluated methods. Current models are black boxes. Explainability techniques such as attention visualization, Grad-CAM, feature importance analysis could reveal which image regions and statistical properties drive detection, improving trust and enabling targeted defense refinement.

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