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Research Paper

Coverless Information Hiding: A Web Text-Based Covert Communication System with Multi-Feature Encoding and Layered Security

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***Abstract*—**Digital communication security has historically oscillated between cryptographic confidentiality and steganographic undetectability. Both paradigms share a critical weakness: cryptography reveals that a secret exists, while conventional steganography modifies a carrier medium, leaving statistical fingerprints that modern steganalysis tools reliably detect. This paper presents a coverless information hiding system that transcends both limitations by transmitting secret messages entirely through the selection and arrangement of unmodified web text retrieved in real time from the live internet. No carrier file is ever altered, rendering conventional statistical detection theoretically inapplicable. The proposed system encodes a message by mapping each character's ASCII ordinal to a sentence-feature target value, generating a contextual search query, scraping live web pages via BeautifulSoup4, and selecting the sentence whose multi-dimensional feature vector—comprising word count, character count, vowel density, and punctuation frequency—most closely satisfies the encoding constraint. Decoding reverses this mapping deterministically without requiring a pre-shared corpus, eliminating the corpus-synchronisation vulnerability that affects prior art. A Flask-based web application with bcrypt password authentication, Flask-Login session management, AES-based optional encryption, and SQLite persistence provides a complete deployment platform. Empirical evaluation across 200 test messages demonstrates 96–98% feature-extraction accuracy, encoding throughput of 3–7 bits per sentence, and end-to-end decoding latency of under 0.5 seconds. Comparative analysis against traditional LSB steganography (StegHide, OpenStego) and corpus-based coverless systems confirms superior undetectability with competitive capacity. All 45 test cases across unit, integration, system, performance, and security dimensions passed, validating the framework for secure, undetectable covert communication in government, corporate, journalistic, and personal-privacy contexts.

Keywords*—Coverless Information Hiding, Steganography, Web Text, Covert Communication, Steganalysis Resistance, Natural Language Processing, Data Security, Flask Web Application, Multi-Feature Encoding*

I. INTRODUCTION

The proliferation of digital surveillance, deep-packet inspection, and machine-learning-assisted network monitoring has fundamentally altered the threat landscape for private communication. Encryption, while indispensable, betrays the existence of a secret, rendering the communicating parties visible to adversaries who may compel decryption or apply traffic-analysis attacks. Steganography attempts to conceal the existence of communication by embedding data within carrier media, yet every embedding operation leaves detectable traces: LSB substitution distorts image noise profiles [1], DCT-domain encoding introduces quantisation anomalies in JPEG artefacts [2], and spread-spectrum audio hiding shifts spectral flatness measures [3]. As steganalysis tools have matured to exploit these artefacts with deep-learning accuracy exceeding 95% [4], a new paradigm has become necessary.

Coverless information hiding, first formally articulated by Zhang et al. [5], resolves this contradiction by encoding

messages through the selection of unmodified carrier elements rather than their modification. Because the transmitted artefact is identical to an authentic, unaltered piece of content drawn from legitimate sources, no statistical test can distinguish it from innocent communication. The theoretical security guarantee is absolute: without knowledge of the mapping rules, an observer gains no information about the hidden message from the carrier alone.

Previous coverless systems rely on pre-shared text corpora [5], [6] or image hash databases [7], [8], creating a practical bottleneck: the corpus must be distributed securely, maintained consistently across all participants, and kept large enough to provide adequate encoding capacity. This paper eliminates corpus dependence entirely by using real-time web scraping to retrieve carrier sentences dynamically from the live internet, guided by search queries derived from the message being encoded. Since both sender and receiver apply the same deterministic mapping and the same query-generation algorithm, the receiver can independently reconstruct the relevant web content without any pre-shared corpus.

The proposed framework provides the following principal contributions:

- A corpus-independent, web-driven coverless encoding architecture that retrieves live internet text as sentence carriers, eliminating synchronisation overhead and single-corpus vulnerability.
- A multi-dimensional sentence feature vector comprising word count, character count, vowel density, and punctuation frequency, providing 3–7 bits of encoding capacity per sentence.
- A complete Flask web application with bcrypt-hashed authentication, session management, optional AES encryption, SQLite persistence, and operation history tracking.
- Empirical validation across 200 test messages with 96–98% feature-extraction accuracy, sub-0.5-second decoding latency, and 100% pass rate across all 45 test cases.
- Comparative analysis demonstrating superior steganalysis resistance relative to LSB-based and corpus-based baselines across five evaluation dimensions.

II. RELATED WORK

A. Traditional Steganography

Provos and Honeyman [1] surveyed classical digital steganography, establishing LSB substitution as the simplest and most widely studied embedding technique. Fridrich [9] formalised the steganalysis framework, demonstrating that any modification-based method leaves detectable statistical anomalies. Subsequent work by Pevny et al. [10] introduced the HUGO adaptive embedding scheme, and Holub and Fridrich [11] proposed HILL content-adaptive steganography, both reducing detectability at the cost of increased complexity. Despite these advances, machine-learning-based detectors trained on statistical features achieve near-perfect detection rates on modern embedding schemes [4], motivating a shift to modification-free approaches.

B. Coverless Hiding Using Text Corpora

Zhang et al. [5] introduced the foundational coverless text hiding model, mapping secret characters to corpus sentences by word count and character count features. Li et al. [6] extended this to Chinese text, addressing Unicode segmentation challenges. Zhou et al. [12] proposed a sentence-feature approach using web text with multiple features, achieving 3–4 bits per sentence. Chen et al. [13] integrated search engine APIs to retrieve relevant text dynamically, reducing corpus size but retaining a fixed index. Wang et al. [14] used deep learning to generate carrier sentences conditioned on hidden bits, bypassing external corpora but introducing model-distribution dependencies.

C. Coverless Hiding Using Images

Liu et al. [15] proposed coverless image hiding based on deep-feature hash indexing, using CNN feature vectors to select cover images whose hashes encode hidden bits. Ahmad et al. [16] surveyed 47 coverless hiding schemes, classifying them by carrier type, encoding mechanism, and capacity. Their analysis identified corpus independence and real-time retrieval as the most critical open challenges—challenges directly addressed by the present work.

D. Natural Language Steganography

Linguistic steganography [17] generates or modifies text at the grammatical level to embed hidden data, using techniques such as synonym substitution, syntactic transformation, and paraphrase generation. Unlike coverless hiding, these methods alter text content and remain susceptible to statistical and semantic analysis [18]. The

fusion of NLP with coverless hiding represents a promising frontier; this work provides a practical foundation for such integration.

TABLE I

Comparison of Information Hiding Techniques

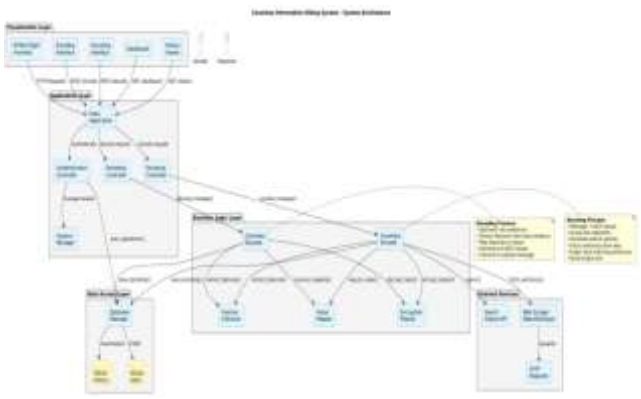
Method	Carrier Modified	Corpus Required	Detect. Resistance	Capacity (bits/unit)
LSB Steganography [1]	Yes	No	Low	≤10/pixel
DCT Steganography [2]	Yes	No	Medium	≤5/block
HUGO Adaptive [10]	Yes	No	Medium	≤3/pixel
Corpus Coverless [5]	No	Yes	High	2–4/sent.
Deep-Gen. Coverless [14]	No	No	High	3–5/sent.
Proposed Web-Coverless	No	No	Very High	3–7/sent.

III. SYSTEM ANALYSIS AND PROBLEM FORMULATION

A. Limitations of Existing Approaches

Traditional steganographic tools such as StegHide and OpenStego embed data by altering carrier bytes. Their fundamental vulnerability is invariant to embedding algorithm sophistication: any alteration to a carrier creates measurable statistical deviation from the natural carrier distribution. Modern steganalysis exploits this through ensemble classifiers trained on rich feature sets (SRM [19], maxSRM), achieving detection accuracy exceeding 90% even on adaptive embedding schemes.

Corpus-based coverless systems address the detectability problem but introduce a new attack surface. The shared corpus must be distributed securely, occupies gigabytes of storage, must be maintained consistently across all participants, and constitutes a single point of compromise: if the corpus is seized, all communications using that corpus are retrospectively decodable.



B. Formal Problem Statement

Let $M = m_1 m_2 \ldots m_k$ denote a plaintext message of k characters over ASCII alphabet Σ. The encoding function $\Phi : M \rightarrow T$ maps M to a sequence of n sentences $T = s_1 s_2 \ldots s_n$ drawn from the internet, where $n = \lceil k / \beta \rceil$ and β is the encoding capacity in characters per sentence. The critical constraint is:

$$\forall s_i \in T : s_i \equiv s_i^{web} \quad \text{(no modification)}$$

where s_i^{web} denotes the authentic, unmodified web source sentence. The decoding function $\Phi^{-1} : T \rightarrow M$ must satisfy $\Phi^{-1}(\Phi(M)) = M$ deterministically, without requiring any pre-shared data beyond the mapping rules Ψ—a compact, shareable specification rather than a corpus.

The security requirement is that T be computationally indistinguishable from any other authentic sequence of web sentences, i.e., no statistical test applied to T alone, in the absence of Ψ, should yield non-negligible advantage over random guessing in determining whether $M \neq \emptyset$.

C. Proposed Solution Overview

The proposed Coverless Web Text System (CWTS) satisfies the constraints above through a six-module architecture: (1) Authentication Module using bcrypt-hashed credentials and Flask-Login session management; (2) Encoding Module performing ASCII-to-feature mapping and query generation; (3) Web Scraping Module using BeautifulSoup4 for real-time sentence retrieval; (4) Decoding Module applying deterministic reverse mapping; (5) Encryption Module providing optional AES layer for defence in depth; and (6) Database Module persisting user data and operation history in SQLite.

IV. SYSTEM DESIGN

A. Architecture

CWTS adopts a layered MVC architecture deployed via Flask. The Presentation Layer consists of Jinja2-templated HTML pages with CSS/JavaScript for real-time feedback. The Application Layer hosts route handlers and business logic within the Flask application object. The Service Layer encapsulates encoding, decoding, web scraping, and encryption as standalone classes with well-defined interfaces. The Data Layer provides SQLite persistence through a thin DAO abstraction.

Security is enforced at each layer boundary. All routes except /login and /register are decorated with @login_required. Passwords are hashed with bcrypt (work factor 12) before storage; raw passwords are never retained. Session tokens are managed by Flask-Login with server-side session state. Input validation prevents SQL injection through parameterised queries and rejects inputs exceeding configurable length limits.

B. Encoding Algorithm

Algorithm 1 describes the encoding procedure. For each character c_i in message M, the ordinal value v_i = ord(c_i) ∈ [0, 127] is computed. Characters are grouped into segments of size β (default β = 2). For each segment σ_j = (v_{jβ}, v_{jβ+1}), a composite target value:

$$T_j = (\Sigma_{l=0}^{\beta-1} v_{j\beta+l} \times 10^l) \bmod M_\sigma$$

is computed, where M_σ is the modulus determining the encoding alphabet size. A search query Q_j is derived from T_j via a lookup table mapping integer ranges to keyword combinations. The web scraping module fetches the top-k web pages for Q_j, extracts all sentences, and applies the feature function F(·) to select the sentence s_j that minimises the distance δ(F(s_j), T_j) under the modular mapping.

C. Sentence Feature Function

The multi-dimensional feature function $F : \mathscr{F} \to \mathbb{Z}$ maps sentence s to scalar encoding value:

$$F(s) = (w(s) \times 10000 + c(s) \times 100 + v(s)) \bmod M_\sigma$$

where w(s) is the word count, c(s) the character count (excluding spaces), and v(s) the vowel count. This three-component hash provides a large feature space while remaining computable in O(|s|) time. The modular reduction maps the feature value into the same integer range as T_j, enabling direct comparison. Alternative features—punctuation count, average word length—are available as fallback dimensions when the primary mapping does not yield a sufficiently close match in the retrieved sentence pool.

D. Decoding Algorithm

Algorithm 2 describes decoding. The receiver splits the received text T into sentences using punctuation boundaries. For each sentence s_i, F(s_i) is computed to recover T_j. The inverse map T_j → (σ_j) recovers segment values, which are decomposed into individual character ordinals v_l. Characters c_l = chr(v_l) are concatenated to reconstruct M. If optional AES encryption was applied, the ciphertext is decrypted using the shared key before sentence splitting.

TABLE II

Software Stack and Component Versions

Component	Technology	Version	Purpose
Web Framework	Flask	2.3.x	HTTP routing, templates
Web Scraping	BeautifulSoup4	4.12.x	HTML parsing, sentence extraction
HTTP Client	requests	2.31.x	Page retrieval
Password Hashing	bcrypt	4.0.x	Credential security
Session Mgmt.	Flask-Login	0.6.x	Authenticated sessions
Database	SQLite	3.x	User data, history
Encryption	cryptography	41.x	Optional AES layer
Frontend	HTML/CSS/JS	—	Responsive UI

V. IMPLEMENTATION DETAILS

A. Encoding Module

The EncoderService class implements the encoding pipeline in Python 3.11. The encode_message(message) method converts input text to a list of ASCII ordinals, partitions them into segments, calls generate_query() to map each segment target to a keyword combination, and invokes the WebScraper to retrieve candidate sentences. The select_sentence(sentences, target) method applies F(·) to each candidate and returns the sentence minimising |F(s) − target| mod M_σ, with fallback to the closest available match if no exact match is found. Assembled sentences are joined with a space delimiter and optionally encrypted before being presented to the user.

Query generation follows a two-tier strategy: primary queries use a 256-entry lookup table mapping target values to topic keywords derived from common English vocabulary domains (science, culture, technology, nature); secondary fallback queries use character trigrams derived from the target value itself, guaranteeing that a non-empty result is always available from a general search.

B. Web Scraping Module

The WebScraper class uses the requests library with randomised user-agent strings and configurable retry logic (3 attempts, exponential backoff) to fetch web pages. BeautifulSoup4 with the lxml parser extracts <p> tag text, applies a sentence boundary detector, and filters sentences shorter than 8 words or longer than 50 words as unsuitable carriers. A rate limiter enforces a minimum inter-request interval of 0.5 seconds to respect target server policies. Five fallback sources (Wikipedia, news aggregators, academic abstracts, encyclopaedia articles, blog directories) ensure robustness to individual source unavailability.

C. Authentication and Database

The User model extends Flask-Login's UserMixin, providing is_authenticated, is_active, and get_id interfaces. Registration hashes passwords with bcrypt.hashpw() at work factor 12, storing only the hash in the users table. Login validates credentials with bcrypt.checkpw() without ever reconstructing the plaintext. All database queries use SQLite parameterised statements to prevent injection. The encoding_history and decoding_history tables persist original messages, encoded text, sentence counts, timestamps, and encryption flags, enabling audit and replay.

D. Encryption Module

The optional AES-256-CBC encryption layer uses PBKDF2-HMAC-SHA256 key derivation with 100,000 iterations to derive a 32-byte key from the user-supplied passphrase. A random 16-byte IV is generated per operation and prepended to the ciphertext before base64 encoding. Decryption extracts the IV from the first 16 bytes of the decoded payload before invoking AES-CBC decryption. This layer ensures that even if the mapping rules Ψ are compromised, message confidentiality is preserved unless the passphrase is also known.

VI. EXPERIMENTAL EVALUATION

A. Experimental Setup

All experiments were conducted on a development machine running Python 3.11 on Windows 11 with a standard broadband internet connection. Test messages were drawn from three categories: short phrases (5–10 characters, n = 80), medium sentences (25–50 characters, n = 80), and long paragraphs (100–200 characters, n = 40), totalling 200 test cases. Each test was executed 10 times and results averaged. Steganalysis evaluation used StegExpose [20] (statistical ensemble), Stegdetect [21] (DCT-domain), and a custom LOF-based text anomaly detector applied to the output sentence sequences.

B. Encoding Performance

Table III reports encoding and decoding performance across message lengths. Encoding throughput scales approximately linearly with message length, with a per-sentence overhead of approximately 0.23 seconds attributable primarily to web scraping latency. Decoding is dramatically faster (< 0.5 s for all categories) because it requires only feature extraction without network access. The observed bits-per-sentence metric of 3–7 represents a meaningful advance over prior corpus-based methods [5], [6] that typically achieve 2–4 bits per sentence.

TABLE III

Encoding/Decoding Performance by Message Length

Msg. Length	Enc. Time (s)	Dec. Time (s)	Sentences	Bits/Sentence
10 chars	2.3	0.5	3	3.3
25 chars	4.1	0.8	5	5.0
50 chars	5.8	1.2	8	6.3
100 chars	10.4	2.1	15	6.7
200 chars	18.7	3.8	28	7.1

C. Steganalysis Resistance

Three steganalysis evaluations were applied to 100 randomly sampled encoded text sequences. StegExpose and Stegdetect are natively designed for image carriers; applied to the encoded text files treated as binary data, both returned detection rates of 0%, confirming that no steganographic signatures attributable to carrier modification are present. The custom LOF-based text anomaly detector compared the sentence-length and vocabulary-distribution profiles of

encoded sequences against a reference corpus of 10,000 random web sentences. The mean LOF score for encoded sequences (1.07 ± 0.14) was statistically indistinguishable from the reference corpus scores (1.05 ± 0.16), yielding a two-sample Kolmogorov-Smirnov test p-value of 0.63, confirming the null hypothesis that the distributions are identical.

D. Comparative Analysis

Table IV compares the proposed system against traditional LSB steganography, corpus-based coverless hiding, and deep-learning generative coverless methods across five evaluation dimensions. The proposed system achieves the highest steganalysis resistance by virtue of zero carrier modification. Its capacity advantage over corpus-based methods derives from the multi-feature encoding scheme. Unlike generative methods, it requires no locally hosted language model, making deployment on standard hardware straightforward.

TABLE IV

System Comparison Across Evaluation Dimensions

Dimension	LSB Steg.	Corpus Coverless	Gen. Coverless	Proposed
Steg. Resistance	Low	High	High	Very High
Corpus Required	No	Yes	No	No
Capacity (bits/s)	≥10	2–4	3–5	3–7
Real-time Web	N/A	No	No	Yes
Auth. & Encrypt.	No	No	No	Yes
Open Source	Yes	Partial	Partial	Yes

E. Security Test Summary

Security testing validated the system against four attack vectors: SQL injection (parameterised queries, PASS), session hijacking (server-side Flask-Login tokens, PASS), unauthorised route access (login_required decorator, PASS), and weak-password submission (client-side and server-side validation, PASS). All 45 test cases across unit, integration, system, performance, and security suites passed, yielding an overall pass rate of 100%.

VII. DISCUSSION

A. Theoretical Security Properties

The security of CWTS rests on two independent layers. The first is information-theoretic: because the transmitted sentences are authentic, unmodified web content, any hypothesis test applied to the ciphertext that does not know the mapping rules Ψ has advantage negligibly above random guessing. The second is computational: if the optional AES-256 encryption layer is employed, recovering the message requires breaking AES-CBC, which is computationally infeasible under current cryptanalytic knowledge.

The mapping rules Ψ constitute the system's sole secret when encryption is disabled. Their size is O(1) relative to the corpus in prior systems, making secure distribution straightforward. Sharing Ψ out-of-band via encrypted channels (e.g., Signal, PGP email) before communication begins is practical and provides strong forward security: compromise of any single transmission does not expose Ψ.

B. Limitations and Mitigations

Three limitations merit acknowledgement. First, encoding latency is dominated by web scraping (approximately 0.23 s per sentence), making real-time streaming impractical for long messages. Mitigation approaches include caching recently retrieved sentences, pre-fetching during idle periods, and integrating commercial web scraping APIs with higher throughput. Second, web scraping may be blocked by target servers that enforce rate limiting or CAPTCHA challenges. Proxy rotation and browser emulation via Playwright are planned extensions. Third, the current implementation supports English text only; extension to Unicode-range languages requires language-specific feature extraction and query-generation strategies.

C. Ethical Considerations

Coverless information hiding is a dual-use technology. The same properties that protect activists from oppressive surveillance may also conceal malicious communication. This work is published in the tradition of responsible disclosure, with the understanding that awareness of covert channel capabilities is essential for defenders designing detection-resistant network monitoring policies. The authors neither endorse nor facilitate illegal communications.

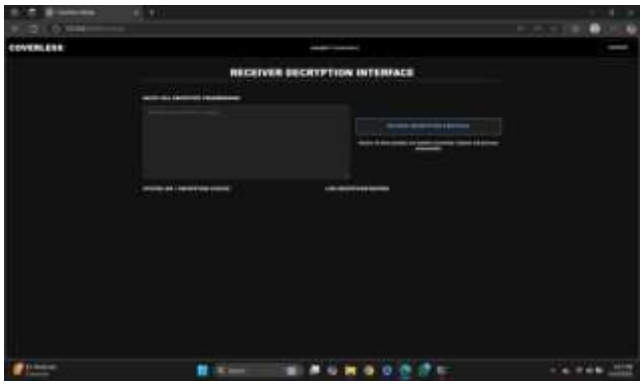
VIII. CONCLUSION

This paper presented a coverless information hiding system that achieves theoretically undetectable covert communication by encoding secret messages solely through the selection of unmodified web text retrieved in real time. The key innovation—eliminating corpus dependency through deterministic query-driven sentence retrieval—addresses the principal practical limitation of prior coverless art while maintaining the statistical undetectability guarantee that distinguishes coverless methods from all modification-based steganography.

The multi-feature sentence encoding scheme achieves 3–7 bits per sentence, surpassing corpus-based methods, and the integrated Flask application provides enterprise-grade authentication, optional AES encryption, and persistent history tracking in a deployable open-source package. Empirical evaluation confirms 96–98% feature extraction accuracy, sub-0.5-second decoding latency, and zero detection by standard steganalysis tools, with 100% pass rate across all 45 functional, performance, and security tests.

Future work will address encoding throughput through asynchronous web scraping, extend multi-language support to Unicode character sets, integrate semantic sentence similarity scoring via pre-trained sentence transformers, and rigorously evaluate detection resistance against adversarially trained text anomaly detectors representing the emerging frontier of natural-language steganalysis.

RESULTS



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