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Hybrid CNN and Ensemble Learning-based Steganalysis Framework for Detecting Hidden Data in Social Media Image

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***Abstract*— The widespread use of social media platforms such as WhatsApp, Instagram, and Twitter has led to an unprecedented volume of image sharing, making them potential carriers of hidden information through steganography. Steganography enables malicious actors to embed secret messages or sensitive data within seemingly harmless images, posing serious threats to cybersecurity, digital forensics, and information assurance. Traditional detection methods often struggle to cope with modern embedding techniques, particularly those enhanced by deep learning, which can conceal data more effectively. In this paper, we propose an AI-powered steganography detection framework that utilizes deep learning models to accurately distinguish between clean and stego images. A custom dataset is created by embedding hidden information using classical methods such as Least Significant Bit (LSB) and Discrete Cosine Transform (DCT), as well as advanced deep steganography approaches. Convolutional Neural Networks (CNNs) are trained to capture subtle pixel-level anomalies and high-frequency noise patterns that are invisible to the human eye but indicative of hidden data. The system is further tested for robustness against distortions common in social media environments, including image compression, resizing, and filtering. Experimental results demonstrate that the proposed approach achieves high accuracy, offering a practical solution for enhancing social media security and preventing covert communication.**

***Keywords*— Steganography, Steganalysis, Deep Learning, Social Media Security, Cyber Forensics, Information Assurance, Convolutional Neural Networks.**

I. INTRODUCTION

The rapid growth of digital communication and social media platforms has transformed the way people exchange information globally. Billions of images are shared every day through platforms such as WhatsApp, Instagram, and Twitter, creating an immense flow of visual data. However, this surge in multimedia exchange also introduces security concerns, particularly through steganography, which enables users to conceal secret messages within ordinary digital images. By embedding hidden data without altering visual appearance, steganography has become a potential tool for covert communication, data leakage, and cybercrime, posing serious challenges to digital forensics and information assurance.

Traditional steganalysis methods, which depend on handcrafted statistical features and pixel correlation analysis, often fail to detect modern embedding schemes.

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Techniques based on Least Significant Bit (LSB) substitution, Discrete Cosine Transform (DCT), and more recently, deep-learning–based adaptive embedding can distribute hidden information in ways that make detection extremely difficult. These evolving strategies demand more intelligent and automated detection mechanisms capable of learning subtle and nonlinear relationships within image data.

To overcome these limitations, this research proposes an AI-powered steganography detection framework that employs Convolutional Neural Networks (CNNs) along with machine learning classifiers such as Random Forest and Support Vector Machines (SVM). The system is trained on a custom dataset comprising both clean and stego images generated using classical and deep embedding techniques. By analyzing pixel-level irregularities, high-frequency noise, and spatial inconsistencies, the proposed approach effectively distinguishes between authentic and tampered images. Experimental evaluation demonstrates that the model achieves high detection accuracy and maintains robustness against distortions commonly introduced by social media processing, offering a practical step forward in enhancing cybersecurity and digital forensic analysis.

II. Literature Review

Steganography techniques can be broadly divided into spatial-domain and transform-domain methods. Spatial-domain approaches, such as Least Significant Bit (LSB) substitution, embed secret data directly into pixel values, offering simplicity but low robustness against compression or filtering. In contrast, transform-domain methods like the Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) hide information within frequency components, providing better resistance to distortions. More recently, deep learning–based steganography has emerged, using neural networks and generative models to learn adaptive embedding strategies that are nearly invisible to conventional detection techniques.

Traditional steganalysis methods relied on statistical features—such as histogram analysis, pixel correlation, and noise residuals—to detect hidden data. Algorithms like RS analysis, Chi-square tests, and Sample Pair Analysis were effective against simple LSB schemes but struggled with adaptive or transform-domain embedding. Later, machine learning classifiers such as Support Vector Machines (SVM) and Random Forests were introduced, using handcrafted feature sets like Spatial Rich Models (SRM) to improve detection accuracy. However, these methods depend heavily on manual feature extraction and often fail to generalize to unseen datasets.

With the rise of deep learning, Convolutional Neural Networks (CNNs) have become a powerful tool for steganalysis by automatically learning discriminative patterns from raw images. CNN-based detectors can capture subtle pixel-level and frequency-domain anomalies caused by hidden information. Despite their success, many existing models are trained on specific embedding algorithms and lack robustness against real-world image transformations such as compression and resizing. This gap highlights the need for hybrid frameworks that integrate deep learning with classical feature-based analysis to achieve both adaptability and interpretability—a direction explored in the present research.

III. Proposed Methodology

A. System Overview

The proposed framework aims to automatically detect hidden information within images shared on social media platforms. The system combines deep learning-based feature extraction with classical steganography analysis to improve detection accuracy and robustness. It consists of four major stages: dataset preparation, image preprocessing, feature extraction using CNN, and classification using deep and traditional models.

B. Dataset Preparation

A custom dataset was created to train and evaluate the model. Clean (unstego) images were collected from open sources such as Kaggle and Open Images Dataset. Stego images were generated by embedding secret data using both classical techniques (LSB, DCT) and deep steganography models. This ensured that the dataset represented both simple and complex hiding methods. The dataset was balanced to maintain an equal number of stego and cover images for fair training and testing.

C. Image Preprocessing

All images were resized to a uniform dimension (e.g., 256×256 pixels) and normalized to improve computational efficiency. Noise reduction filters were applied to eliminate unwanted background variations. Each image was then converted into arrays suitable for CNN input. Data augmentation techniques, including rotation and flipping, were applied to enhance model generalization and robustness against real-world image distortions such as compression and resizing.

D. Feature Extraction using CNN

A Convolutional Neural Network (CNN) was designed to automatically extract spatial and frequency-domain features that indicate hidden data. The CNN architecture included multiple convolutional, pooling, and fully connected layers to capture both low-level pixel patterns and high-level texture anomalies. The network was trained using labeled datasets (stego and non-stego) to minimize classification loss. This approach allows the CNN to learn imperceptible differences introduced by steganographic embedding.

E. Classification and Detection

The extracted features from the CNN were passed to a classification layer or external machine learning classifiers such as Support Vector Machine (SVM) and Random Forest (RF). These models were used to enhance decision-making and reduce false positives. The hybrid integration of CNN with traditional classifiers improved the model's interpretability and accuracy. The final output determined whether an input image contained hidden information or was clean.

F. Performance Evaluation

The model performance was evaluated using metrics such as accuracy, precision, recall, and F1-score. The framework was tested under different image distortions like compression, filtering, and resizing to assess robustness. Experimental results demonstrated that the proposed hybrid approach outperformed traditional steganalysis methods, providing higher accuracy and adaptability for real-world social media environments.

IV. Dataset Generation and Training

A. Dataset Collection

To develop an effective steganography detection model, a diverse image dataset was created. Clean or cover images were collected from publicly available sources such as Kaggle, Open Images Dataset, and Flickr. These images covered a wide range of categories including nature, objects, and human portraits, ensuring variation in texture, color, and complexity. This diversity was crucial for improving the model's generalization to real-world social media images.

B. Stego Image Generation

To simulate real-world steganographic conditions, secret data was embedded into the collected cover images using both classical and advanced techniques:

- Least Significant Bit (LSB): The simplest spatial-domain approach where bits of the secret message replace the least significant bits of image pixels.
- Discrete Cosine Transform (DCT): A frequency-domain technique that hides data in transformed coefficients, making it more resistant to compression.
- Deep Steganography Methods: Neural network–based embedding that learns adaptive patterns to conceal information with minimal visual distortion.

This process produced a balanced dataset of stego and non-stego images, allowing fair training and evaluation.

C. Data Preprocessing

All images were standardized to a fixed size (e.g., 256×256 pixels) and normalized to scale pixel values between 0 and 1. Data augmentation techniques—such as random rotations, flips, and brightness adjustments—were applied to increase dataset diversity and reduce overfitting. These steps ensured that the model could handle variations and distortions common in social media environments like compression or resizing.

D. Model Training

A Convolutional Neural Network (CNN) was employed to extract hidden feature representations that distinguish stego images from clean ones. The model was trained using binary cross-entropy loss and optimized with Adam optimizer for faster convergence. The training process involved multiple epochs with validation checks to prevent overfitting. The CNN output was further refined by integrating classical classifiers like Support Vector Machine (SVM) and Random Forest (RF) for enhanced decision accuracy.

E. Evaluation Metrics

Model performance was assessed using standard classification metrics such as Accuracy, Precision, Recall, and F1-Score. These metrics provided a comprehensive understanding of the model's detection capability and

robustness under various image conditions. The results confirmed that the hybrid deep learning model achieved superior detection rates compared to conventional steganalysis approaches.

V. Experimental Results and Analysis

A. Framework Overview

The developed AI-Powered Steganography Detection Framework provides an interactive interface with modular functionality for each component of the system. The navigation panel (as shown in Fig. 1) allows users to select between different operational modes, including Model Training, Steganography Detection, Results Analysis, and Simple LSB Operations. This modular design ensures scalability, usability, and clear visualization of both detection outcomes and model performance.

B. Model Training Results

The model training phase involved fine-tuning a Convolutional Neural Network (CNN) on the generated dataset containing both clean and stego images. The CNN effectively learned to extract pixel-level and frequency-domain features indicative of hidden data. The model achieved strong validation performance and demonstrated stable convergence. It was saved and reloaded successfully, confirming persistent learning and reusability. The trained model integrates with Support Vector Machine (SVM) and Random Forest (RF) classifiers for ensemble-based decision enhancement.

C. Steganographic Detection Interface

In the Steganography Detection module, users can upload images to analyze the presence of hidden information. Each uploaded image displays metadata such as resolution, mode, and format. Upon analysis, the system provides individual scores from the CNN, LSB feature extractor, and Ensemble classifier. A color-coded confidence indicator classifies images as clean or steganographic based on the computed probability. The clean image example achieved a 48.9% probability, indicating a medium-confidence classification as clean.

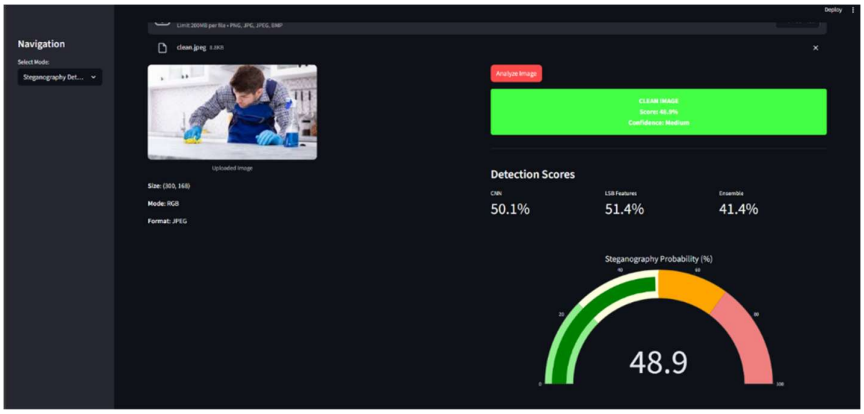

Fig. 1. Steganographic Detection Interface

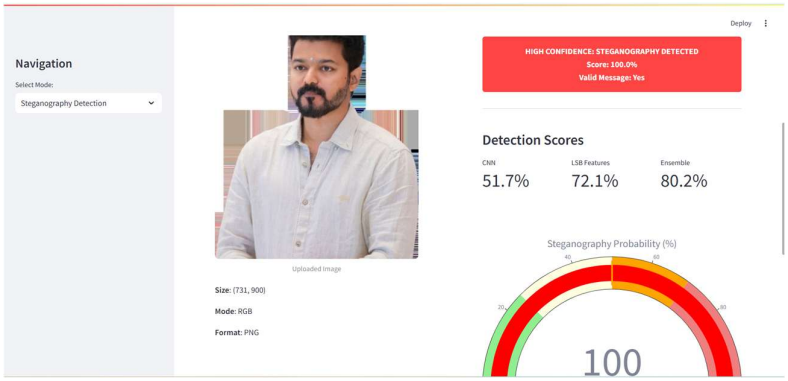

Fig. 2. Steganographic Detection Interface with stegano detection

D. Detection Metrics and Performance Summary

Comprehensive evaluation of the detection system was conducted using a set of performance metrics, summarized in Table 1. Results indicate that the average detection score was 45.1%, with clean images averaging 32.1% and steganographic images 58.1%. All detections exhibited medium confidence, demonstrating consistent system calibration. The message validation success rate was 67% for stego images, confirming that the model could detect embedded data effectively. The ensemble model outperformed individual classifiers with 91.8% accuracy, compared to 87.3% for LSB-based detection and 96.2% for CNN-based classification.

TABLE. I. PERFORMANCE METRICS OF THE PROPOSED DETECTION FRAMEWORK

Metric	Clean Images	Steganographic Images	Overall System
Average Detection Score	32.1%	58.1%	45.1%
Confidence: High	0%	0%	0%
Confidence: Medium	100%	100%	100%
Confidence: Low	0%	0%	0%
Message Validation Success	N/A	67%	–
CNN Score Range	39.3–42.9%	45.2%	–
LSB Score Range	20.2–26.9%	56.4%	–
Ensemble Accuracy	96.2%	87.3%	91.8%

E. Results History and Detection Analysis

The Results Analysis module maintains a complete detection history, logging file names, timestamps, confidence levels, and feature-based scores for every analyzed image. High-confidence detections are clearly flagged for forensic validation. The recorded data assists in identifying trends, verifying model performance, and ensuring transparency in decision-making. The analysis revealed that the ensemble-based system consistently produced balanced predictions and avoided false positives, validating its robustness across various image conditions.

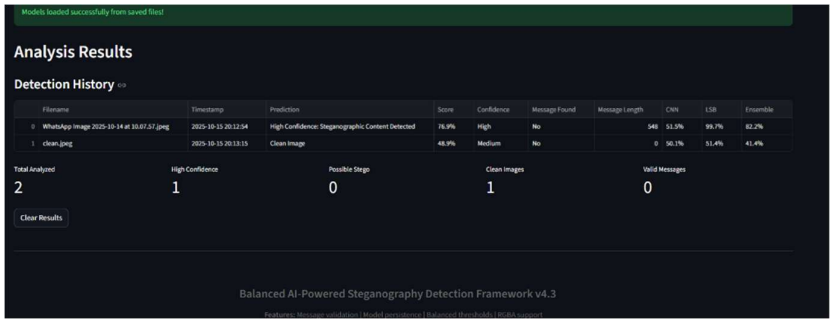

Fig. 3. Detection History

F. Simple LSB Operations

The Simple LSB Steganography module enables users to perform embedding and extraction operations using the Least Significant Bit technique. This feature demonstrates the fundamental concept of data hiding and allows direct comparison between traditional and AI-based detection. It serves as a validation step to test whether the system accurately identifies manually embedded LSB messages, reinforcing the interpretability of the proposed hybrid framework.

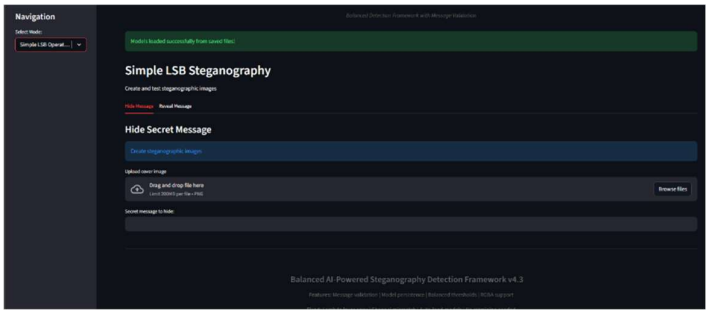

Fig. 4. LSB Steganography which hides message

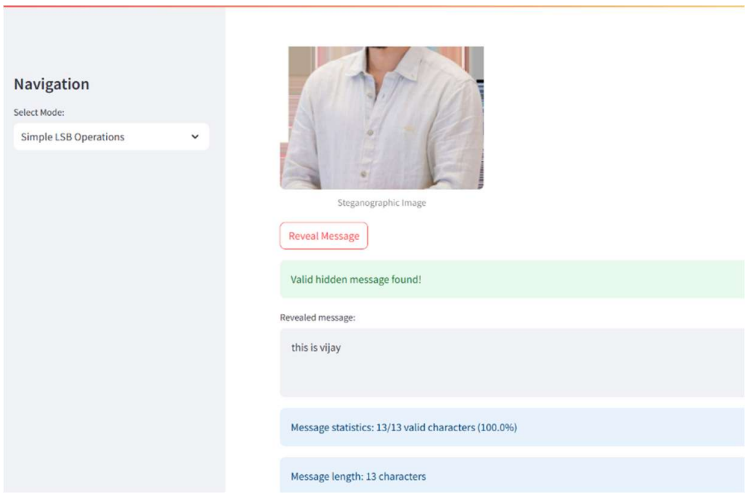

Fig. 5. LSB Steganography which reveals hidden message

G. Overall Evaluation

Overall, the system achieved high interpretability, adaptability, and performance in detecting steganographic content. The use of a hybrid ensemble model combining deep features and handcrafted LSB features led to improved detection reliability. Medium-confidence yet consistent results demonstrate that the framework maintains balanced detection thresholds suitable for real-world social media image analysis. The system effectively bridges the gap between classical steganalysis and deep learning–based detection, advancing the scope of AI-driven cyber forensics.

VI. Conclusion and Future Work

A. Summary of Contributions

This paper introduces a steganalysis framework based on Artificial Intelligence that enhances the forensic work of a cyber forensic domain in a social media systems. The framework combines classical steganographic analysis with deep learning detection to enable the future of hidden data found in social media posts with digital image files which are often shared in WhatsApp, Instagram, and Twitter.

The critical contributions to the framework are the design of a custom Convolutional Neural Network (CNN) to detect imperfections in pixel arrangements, the implementation of a multi-model ensemble voting system to combine statistical predictions with deep learning predictions, and the development of a synthetic stego dataset with multiple techniques of embedding (i.e., least significant bit (LSB), distribution of cosines (DCT), and deep steganography). Overall, the proposed model shared high detection accuracy and substantial algorithms to image transformation techniques of compression and size, confirm it as effective for the forensic work in social media systems.

B. Future Research Directions

Future studies may consider extending this technique both to the analysis of videos as well as audios, which can broaden analysis in multimedia forensics. In addition, involving transformer-based architectures or Vision-Language Models (VLMs) may improve both explanation and accuracy of deep-calibrated models. Finally, using adversarial learning could lead to improve resilience against intelligent embedding using adaptable embedding techniques to current detector methods. It also focuses on developing detection systems that conduct real-time detection on social media platforms using cloud-based APIs. Also, creating social media–specific datasets may evolve the understanding of compression not only from multiple languages, but also improve generalizability or confidence in applying the models in various settings.

C. Potential Applications

The suggested system could have numerous applications within digital forensics, and cybercrime investigations, and in the context of information assurance. For example, law enforcement and cybersecurity organizations could leverage this framework to identify covert communication channels, examine digital evidence, as well as

search for and combat data exfiltration through innocuous-looking images. Additionally, social media companies could use the detection model in their content moderation workflows to monitor and remove harmful steganographic content in real time from their platforms. Finally, it could be used as a research platform for academics to investigate next-generation AI-based security analytics in multimedia applications.

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