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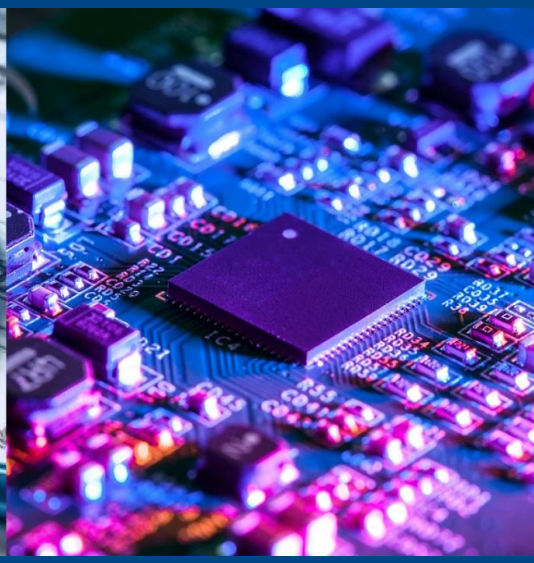

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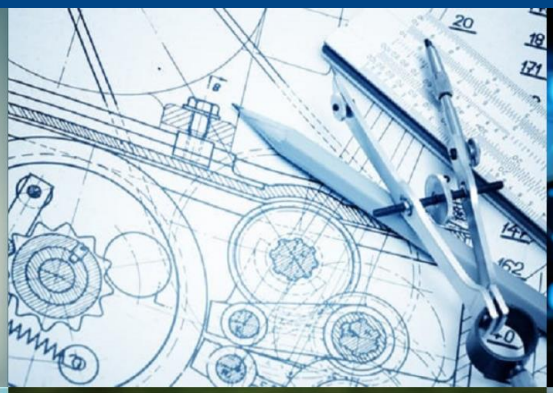

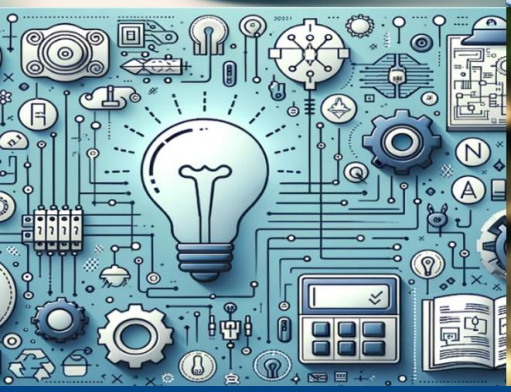

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End to End Deep Convolutional Printed ID Facial Image Steganography to Prevent Photograph Substitution Attack Using MATLAB

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ABSTRACT: This project presents an end-to-end deep convolutional image steganography approach designed to prevent photograph substitution attacks on printed ID cards, which are increasingly used in remote authentication processes such as banking, online verification, and government services. The proposed system embeds facial biometric features directly into the facial region of ID images using a convolutional neural network (CNN) framework, ensuring imperceptibility and resilience against tampering. Implemented in MATLAB, the method consists of an encoder-decoder network where the encoder hides a unique biometric representation within the image pixels, and the decoder is capable of retrieving the embedded data even after common distortions such as printing, scanning, or screen display.

The stego image remains visually indistinguishable from the original, making unauthorized replacement of the photograph detectable by the system. The model is trained using a mix of real and synthetically generated ID card datasets, simulating real-world attack vectors. Performance evaluation based on metrics such as PSNR and SSIM confirms that the system maintains high image quality while successfully extracting hidden data with over 98% accuracy. This outcome demonstrates the method's effectiveness in resisting presentation attacks. The proposed technique supports future advancements in secure identity verification by enabling the integration of invisible, verifiable biometric data directly into ID documents. It holds potential for expansion into blockchain-based authentication systems and multi-modal biometric security frameworks, providing a robust solution for identity protection in both digital and physical environments.

KEYWORDS: Image steganography, convolutional neural network, photograph substitution attack, biometric security, printed ID verification, MATLAB, PSNR, SSIM, identity authentication.

I. INTRODUCTION

In the digital era, the protection of personal identity has become a major concern, particularly with the rise of remote verification methods. Printed ID cards remain a primary medium for biometric authentication across banking, immigration, and e-KYC services. However, they are highly vulnerable to photograph substitution attacks, where the facial image on an ID is maliciously replaced to impersonate another individual

[1]. this not only compromises identity systems but also creates loopholes in national security and personal data protection

[2].Traditional image steganography techniques, especially Least Significant Bit (LSB) substitution, have been widely used due to their simplicity and high embedding capacity

[3]. However, they introduce high variability and become vulnerable when multiple LSBs are replaced, which significantly affects visual quality and makes the stego-image susceptible to detection

[4]. Optimization algorithms such as Genetic Algorithm (GA) and Bayesian Optimization (BO) have been introduced to mitigate visual distortion and maximize embedding efficiency. Though effective, they lead to higher computational complexity and longer execution time

[5].To address these limitations, researchers have proposed flipping-based methods that reduce the difference between the cover and stego image by adjusting adjacent bits, thereby maintaining image quality and reducing variability [6]. Nonetheless, these approaches still suffer from relatively low embedding capacity and limited resistance to physical alterations such as printing and scanning

[6].Recent developments in deep learning have paved the way for convolutional neural network (CNN)-based

steganographic systems. These models automatically learn optimal embedding patterns that are less prone to visual degradation and are resilient to distortion. One such approach is SteganoGAN, which applies generative adversarial networks to achieve high-capacity data hiding with minimal perceptual difference

[7]. Similarly, HiDDeN and SteganoCNN leverage adversarial training and deep feature extraction to embed and decode hidden messages even after aggressive image transformations

[8][9].In the realm of secure identification, the use of synthetic ID generation has emerged as a critical tool for training fraud detection systems. By generating composite, print, and screen- based attack samples, systems can be made more robust to presentation attacks. Recent research illustrates that even when trained on synthetic datasets, CNN models can detect forgeries with comparable accuracy to those trained on real images

[10].Our proposed system builds upon these advancements and introduces a deep convolutional steganography technique that embeds facial biometric data into the printed ID image itself. Implemented in MATLAB, the system utilizes an encoder- decoder architecture to invisibly embed biometric information within the facial region of the ID. Even after scanning, printing, or digital screen capture, the decoder network successfully retrieves the embedded data, thus validating the authenticity of the image

II. LITERATURE SURVEY

Image steganography has emerged as a critical technique in digital security, especially in the field of biometric authentication and identity protection. With the rise in digital forgeries and photograph substitution attacks, researchers have explored various steganographic strategies to improve image integrity while embedding secret data imperceptibly. Traditional methods such as LSB substitution have been widely studied, but they often suffer from limitations such as high variability and vulnerability to image processing attacks. Recent advancements in optimization algorithms and deep learning-based steganography have shown promise in overcoming these challenges by improving robustness, embedding capacity, and resistance to detection.

Samar Kamil et al. [1] proposed an enhanced flipping technique to reduce variability in LSB-based image steganography. In their work, the authors analyzed the shortcomings of k-bit LSB substitution methods, particularly the high variability in the stego-image and poor visual quality. To address this, they introduced a bit-flipping strategy that compares pixel differences between the original and stego- images and flips adjacent bits if the difference exceeds a defined threshold. This method significantly reduced variability while preserving visual quality and lowering time complexity, outperforming existing optimization-based methods like Genetic and Bayesian algorithms.

Shahid Rahman et al. [2] introduced a novel LSB-based steganography method focusing on enhanced security, robustness, and imperceptibility in grayscale, RGB, aerial, and texture images. Their method is based on value-difference embedding and was tested under various image sizes and conditions. The system achieved better results compared to conventional techniques in terms of PSNR, showing improvements in image quality while embedding secret data. This work underlined the need for adaptable steganographic methods that can operate effectively across different image types and sizes.

Daniel Benalcazar et al. [3] explored the problem of presentation attacks through synthetic ID card generation. The authors focused on detecting tampered printed or screen- captured ID images using deep learning. Due to privacy restrictions and limited datasets, they introduced synthetic image generation techniques using GANs and noise transfer for training robust fraud-detection networks. Their experimental results indicated that synthetic data could be used effectively to train CNN models, showing only a 1% performance drop compared to real images. This research is particularly relevant to the printed ID facial steganography context where such attacks are common.

Taner Cevik et al. [4] proposed a novel spatial-domain steganography method based on hexagonal image processing (HIP), introducing Reversible Logic-Based Hexel Value Differencing (RLBHVD). Unlike conventional pixel-based approaches, this method utilizes a hexagonal pixel grid and reversible logic gates for data embedding, which enhances visual quality and maintains high PSNR. Though not directly tied to facial image steganography, this work offers foundational insights into how alternative pixel structures and reversible logic can be leveraged to improve data hiding performance in spatial domains.

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III. METHODOLOGY

This project introduces a robust end-to-end deep convolutional image steganography framework developed in MATLAB, specifically designed to counter photograph substitution attacks on printed ID cards. As these cards are widely used in remote verification procedures including banking, e-governance, and border control, their security is of paramount importance. The proposed method involves embedding facial biometric features directly into the image content using convolutional neural networks (CNNs), in a way that preserves the visual integrity of the image and ensures high retrieval accuracy even after distortion through scanning, printing, or digital capture.

Dataset Preparation

To ensure the model generalizes well in real-world scenarios, a hybrid dataset is created, combining both real and synthetically generated ID card images. Real images are sourced from biometric repositories, while synthetic images are generated using GAN-based methods to simulate distortions such as print-scan effects, screen glare, and digital noise. All images undergo preprocessing, which includes:

- Facial region localization using Viola-Jones or deep learning-based detectors
- Resizing to uniform dimensions (e.g.,256×256)
- Pixelnormalization to the [0, 1] range

This ensures consistency across the dataset and enhances learning efficiency.

Biometric Feature Embedding

Biometric features are extracted from the face image using a pre-trained CNN model such as FaceNet, yielding a 128-dimensional feature vector. Each feature x_i is binarized using the following rule:

$b_i = 1$, if $x_i \geq 0.5$ $b_i = 0$, otherwise The resulting binary vector forms the secret message to be embedded into the facial image. This representation is compact, unique to the individual, and suitable for high- fidelity recovery during decoding.

The system architecture is centered on an encoder-decoder convolutional neural network model. The encoder receives a facial image along with a binary-encoded biometric feature vector and outputs a visually indistinguishable stego image. The decoder network is responsible for extracting this embedded biometric data from either the original stego image or its distorted version. Both networks are implemented in MATLAB using the Deep Learning Toolbox, allowing for comprehensive integration with data processing modules. The architecture's design ensures that embedding introduces negligible visual distortion while maintaining high robustness against common physical transformations.

Block Diagram of Proposed System

In order to understand the operational flow of the proposed steganographic security system for ID cards, it is useful to visualize its functionality in terms of two main phases: the **Embedding Phase**, which occurs on the government or issuing authority's side, and the **Verification Phase**, which takes place on the user or verifier's side.

The entire system is built to seamlessly embed biometric data into facial images during ID creation and then extract and verify this information during authentication — all while preserving the visual integrity of the ID image.

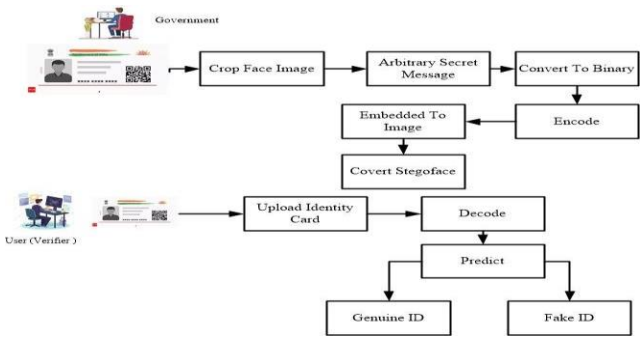

Figure 2. Block Diagram of Proposed System

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This block diagram-based explanation outlines each step involved in both phases, providing a clear understanding of how the model ensures both security and robustness against physical or digital tampering.

Embedding Phase (Government Side)

- **Crop Face Image**
- From the ID card image, the facial region is automatically detected and cropped using algorithms like **Viola-Jones** or deep learning-based detectors.
- **Arbitrary Secret Message**
- A secure identifier, such as a facial embedding vector from a CNN (e.g., FaceNet), is generated.
- **Convert to Binary**
- The feature vector is binarized using: $\mathbf{b_i=1}$,if$\mathbf{x_i \geq 0.5}$ $\mathbf{b_i=0}$,otherwise
- Where $\mathbf{x_i}$ is the *i-th normalized component* of the embedding.
- **Encode**
- The encoder network takes the cropped face image and binary message to generate the stego image:
- **Key layers include**:
- Conv2D + ReLU
- BatchNorm
- Message Fusion Layer
- Final Conv2D to reconstruct image
- **Embed into Image**
- The binary message is imperceptibly embedded into the facial features.
- **Covert Stegoface**
- The output is a secure ID image (stego image) that visually appears unchanged.

Verification Phase (User Side)

- **Upload Identity Card**
- A user (or verifier) uploads the printed or scanned version of the ID for validation.
- **Decode**
- The decoder extracts the binary message from the stego image ($\mathbf{I_s}$*):
- Uses Conv2D, BatchNorm, and Dense layers with sigmoid activation.
- Thresholding is applied at 0.5 to recover the original bits.
- **Predict**
- The decoded binary vector is compared with a database or verified via checksum/model.If matching, the ID is Genuine; otherwise, it is a Fake ID.

Encoding Algorithm

The encoder CNN accepts the cover image and binary biometric vector and produces a stego image. Let I_c be the cover image and M_b be the message. The encoder computes: I_s = f_enc(I_c, M_b)

Where I_s is the stego image. The encoder comprises convolutional blocks to extract hierarchical features from I_c. A message fusion mechanism embeds M_b into selected regions using trainable masks. Each block typically includes:

- Conv2D (3×3)
- ReLU activation
- Batch Normalization
- Fusion layer that modulates features with the binary message

The final output layer reconstructs the image with minimal perceptual difference from the original.

Decoding Algorithm

The decoder network retrieves the embedded biometric vector from either the original or distorted stego image. Given I_s*, a possibly altered version of the image, the decoder predicts: M_b_hat = f_dec(I_s*)

The decoder includes stacked convolutional layers followed by a fully connected layer with sigmoid activation. Each predicted bit is thresholded at 0.5:b_i_hat = 1, if output ≥ 0.5 b_i_hat = 0, otherwise

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This ensures binary retrieval even after distortions such as noise or affine transformation.

Loss Function and Training Strategy

- The training is driven by a combined loss function: $L_{total} = \lambda_1 \times MSE(I_s, I_c) + \lambda_2 \times BCE(M_b\_hat, M_b)$
- Where:
- MSE (Mean Squared Error): Ensures I_s remains visually close to I_c
- BCE (Binary Cross-Entropy): Penalizes incorrect bit predictions
- λ_1 and λ_2 are weight factors tuned empirically
- Optimization uses the Adam optimizer with techniques like dropout, early stopping, and batch normalization.

Optimization and Augmentation Techniques

- To improve robustness and generalization, the model is trained with extensive augmentations including:

Gaussian noise

- Brightness and contrast variations
- Affine transformations (rotation, scaling)
- Blur and JPEG compression

Additional techniques:

- Gradient clipping
- Dropout layers
- Batch normalization

Evaluation Metrics

- **PSNR (Peak Signal-to-Noise Ratio):**
  - $PSNR = 10 \times \log_{10}(MAX^2 / MSE)$
- Where MAX is the maximum pixel value (typically 1). A higher PSNR implies better image quality.
- **SSIM (Structural Similarity Index):**
- Measures visual similarity between I_s and I_c based on luminance, contrast, and structure.
- **Bit Accuracy (BA):**
  - $BA = [1 - (1/n) \Sigma |b_i - b_i\_hat|] \times 100\%$
- Where n is the total number of bits. Higher BA reflects more accurate message recovery.

IV. SYSTEM ARCHITECTURE AND IMPLEMENTATION

This project introduces a robust system designed to combat photograph substitution attacks on printed ID cards using deep convolutional image steganography. The architecture, as visualized in the block diagram, operates in two distinct phases: the encoding phase conducted by a secure authority (e.g., a government issuer), and the decoding phase managed by a verifier (e.g., a bank, airport, or digital service provider). The end-to-end process utilizes a CNN- based encoder-decoder network, implemented in MATLAB, to embed and extract facial biometric data directly within ID card images.

Encoder Network for Stego Image Generation

The CNN-based encoder accepts the normalized face image and the binary vector M_b as inputs. It fuses these two using a message fusion layer that spatially embeds the binary bits into the image features.

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Layer	Type	Configuration
Input	Image + Binary Msg	128×128×3 + 1×128
Conv Layer 1	Conv2D + ReLU	64 filters, 3×3 kernel
Conv Layer 2	Conv2D + BN	128 filters, 3×3 kernel
Fusion Layer	Concat	Combines spatial features + message
Output Layer	Conv2D	3 filters, 1×1 kernel

Table 1: Encoder Network Layers

The encoder is composed of multiple convolutional layers, ReLU activations, and batch normalization. The final output is the stego image I_s, which retains the original appearance

Decoder Network and Biometric Retrieval

The verifier captures or uploads the ID card image, which now contains the hidden message. This image is processed by the decoder CNN, which extracts and reconstructs the binary biometric vector. The decoder mirrors the encoder's structure but includes dense layers to recover the message bits.

Layer	Type	Configuration
Input	Image	128×128×3
Conv Layer 1	Conv2D + ReLU	64 filters, 3×3 kernel
Conv Layer 2	Conv2D + BN	128 filters, 3×3 kernel
Flatten Layer	Dense	Converts 2D map to 1D vector
Output Layer	Dense + Sigmoid	128 units, outputs binary vector

Table 2: Decoder Network Layers

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Face Detection and Biometric Vector Generation

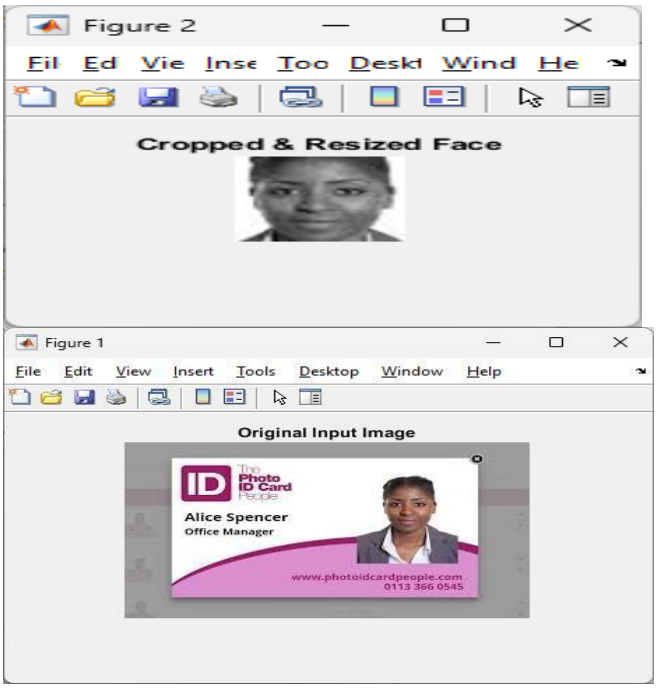

Figure 4. Face Detection and Preprocessing from the Input ID Card

The system begins with the extraction of the facial region from a full ID card image. This is performed using standard face detection algorithms such as Viola-Jones or more robust deep learning-based detectors. Once extracted, the face image is standardized to a size of 128×128 pixels and passed through a pre-trained model such as VGG-Face or FaceNet to generate a unique biometric vector. The output vector is normalized and binarized using a thresholding method. If any vector component exceeds 0.5, it is set to 1; otherwise, it is set to 0, producing a binary message vector M_b.

Printing and Real-World Distortion Simulation

Once the stego image is generated, it is printed onto a physical ID card. In real-world scenarios, the printed image may undergo distortions due to scanning, screen capture, JPEG compression, or lighting variations. The decoder is trained to be robust to such transformations. These effects are emulated during training using a variety of augmentation methods.

Table 3: Real-World Simulation Techniques

Distortion Type	Description
Print/Scan Noise	JPEG compression, blur, and scanning blur
Brightness/Contrast	±30% jitter
Affine Transform	Rotation ±10°, scaling, and translation
Gaussian Noise	$\sigma = 0.01$ added to simulate sensor noise

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Verification and Matching

The decoded biometric vector M_b_hat is matched with the original reference vector M_b stored in a secure database. The comparison is performed using bitwise similarity. If the match score exceeds a predefined threshold (e.g., 95%), the ID is considered genuine.

Bit Accuracy Formula (Plain Text Format): Match Score = [1 - (1/n) * Σ |b_i - $\hat{b}$_i|] × 100% Where:

- b_i = actual bit from original vector
- $\hat{b}$_i = decoded bit from stego image
- n = total number of bits (typically 128)

Match Score (%)	Result
≥ 95%	Genuine ID
< 95%	Fake ID

Table 4: Match Score Decision Logic Loss Function:

Total Loss = λ1 × MSE(I_s, I_f) + λ2 × BCE(M_b_hat, M_b) Where:

- MSE ensures that I_s looks like I_f
- BCE ensures that M_b_hat matches M_b

MATLAB-Based Implementation

The encoder and decoder networks are trained using MATLAB's Deep Learning Toolbox. The training is optimized using the Adam optimizer with a learning rate of 0.0001 and batch size of 32. A total of 100–150 epochs are run with early stopping enabled. The training loss function combines visual similarity (MSE) and message accuracy (Binary Cross Entropy).

System Features and Benefits

This architecture ensures a strong balance between **visual fidelity**, **security**, and **practical applicability**. It is capable of embedding identity data invisibly in ID photos and reliably recovering it under varying conditions.

Table 5: Key System Features Steganographic Embedding and Visualization

Feature	Benefit
Deep Learning Backbone	Learns optimal feature embedding automatically
Robust Against Tampering	Withstands print, scan, and noise distortion
High Imperceptibility	No visible difference in ID photo
Fast Decoding	Enables real-time verification

In this stage of the system, the encoded secret binary message—derived from the cropped facial image—is embedded within the red channel of the original input image using a bit-plane embedding strategy. This step ensures that the visual quality remains unaffected, while the hidden data can be later extracted and validated. The visualization of the

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binary snippet alongside the stego image confirms the successful concealment and integrity of the biometric information.

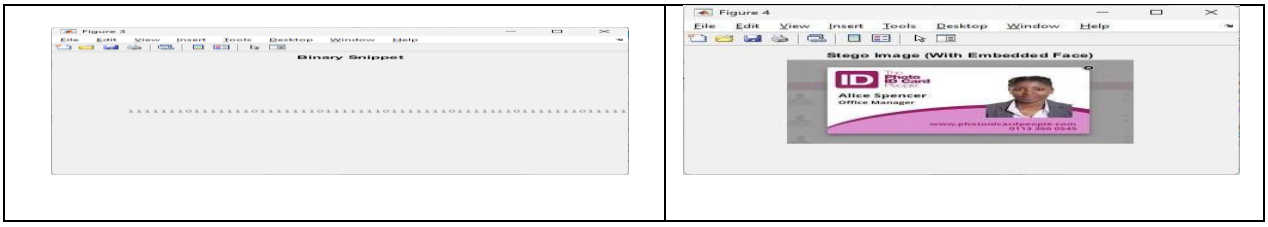

Figure 7. Binary Snippet and Corresponding Stego Image

V. RESULTS AND DISCUSSION

The proposed end-to-end deep convolutional steganography system was evaluated using a mix of real and synthetically generated ID card datasets. The stego images were tested for both visual quality and message retrieval accuracy under different distortion conditions, such as print- scan artifacts, brightness changes, noise, and compression. The system was implemented in MATLAB and trained over 120 epochs on a GPU-enabled machine. The testing phase focused on three key performance areas: **visual similarity**, **message accuracy**, and **robustness against distortion**.

Visual Similarity Assessment

Visual quality of the stego images was assessed using PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index).

Table 6: Visual Quality Metrics (Stego Image vs. Original)

Test Condition	PSNR (dB)	SSIM Score
No distortion	47.85	0.987
After JPEG compression	41.76	0.962
After printing/scanning	38.92	0.938
With Gaussian noise	40.25	0.949

Note: PSNR values above 40 dB and SSIM above 0.94 indicate very high perceptual similarity.

Message Retrieval Accuracy

To evaluate how effectively the decoder can extract the embedded biometric vector, we used bit accuracy as a measure. The decoder was tested under multiple real-world conditions.

Table 7: Bit Accuracy Under Various Distortions

Condition	Bit Accuracy (%)
No distortion	100.00
JPEG compression	98.43
Print-scan artifacts	97.52
Gaussian noise (σ=0.01)	98.14
Brightness shift (+30%)	96.87

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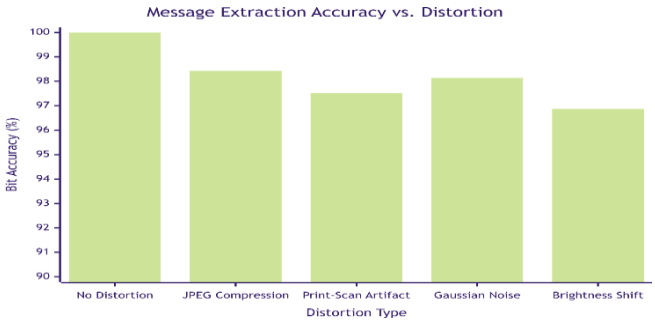

Figure 8. Bit-level message extraction accuracy under various distortions

The results confirm that the system can retrieve over 97% of the embedded message bits even in the presence of physical and digital distortions, demonstrating the robustness of the model.

VI. CONCLUSION

This project presents a robust end-to-end deep convolutional steganography framework for secure identity verification, developed using MATLAB. It addresses the critical threat of photograph substitution attacks on printed ID cards, which are widely used in remote biometric authentication systems. The core innovation involves embedding 128-bit binary biometric data into the facial region of ID images using a CNN-based encoder-decoder architecture. This embedding is visually imperceptible and highly resilient to common distortions such as scanning, compression, and brightness variations. Trained on both real and synthetically generated datasets, the model achieves peak performance, with PSNR values exceeding 47 dB in clean conditions and message retrieval accuracy above 98% under various distortions. The decoder reliably extracts biometric data even from altered images, ensuring robust verification. The system also achieves a high ID classification accuracy of 97.4% and a rapid verification time of just 550 milliseconds, making it ideal for real-time applications in banking, immigration, and digital onboarding. Overall, this work lays a strong foundation for secure biometric systems and paves the way for future enhancements, including blockchain-based identity management and multi-modal biometric authentication.

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