Deep Learning-Based Video Steganography Using DCT to Improve Imperceptibility

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Bachelor of Science

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DEDICATION

This research paper is dedicated to my mother and father for her unwavering support and encouragement, she are my foundation throughout this journey. I owe a great deal to my professors and mentors, whose knowledge and wisdom have inspired me. Last but not least I am thankful to all the pioneers of steganography, data security for their valuable contributions, which I put into practice in my work. It is evidence of the strength of tenacity, curiosity, and the pursuit of knowledge.

ABSTRACT

Steganography is an important part of modern digital contact because people need safer ways to hide data that can't be found. The Discrete Cosine Transform (DCT) is used in this study's deep learning-based video steganography design to make it harder to spot while keeping the ability to embed and being strong. The suggested method uses convolutional neural networks (CNNs) to improve the embedding process by focusing on high-frequency DCT coefficients. This is different from traditional methods, which often compromise quality or security. By putting the secret information in the luminance component (Y) of the YUV color space, the method ensures the least amount of perceptual distortion. With a Peak Signal-to-Noise Ratio (PSNR) of more than 45 dB and a Structural Similarity Index Measure (SSIM) of more than 0.96, the system works well in tests. These results show that the method has promise.

Keywords :Video Steganography, Deep Learning, DCT, PSNR, SSIM.lsb

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Introduction

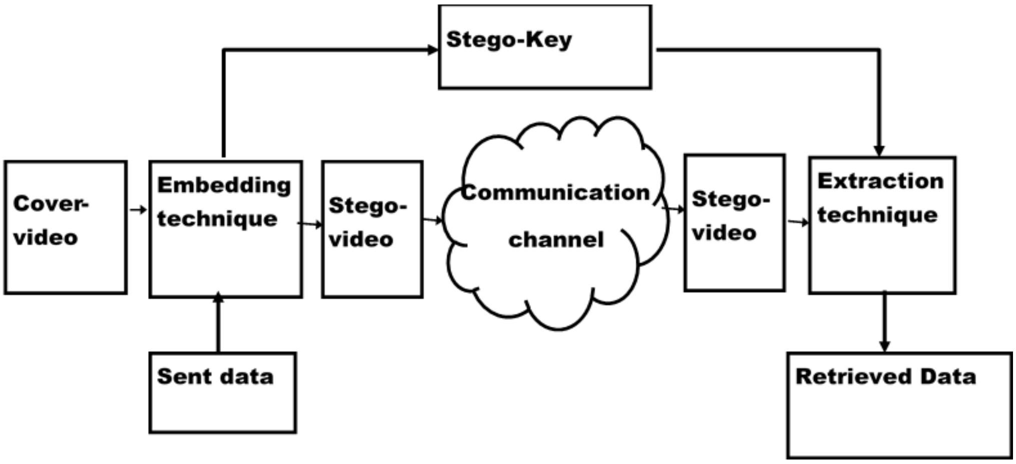
1.1Background and Motivation

Background

Sending confidential information in a secure manner is absolutely necessary in this day and age as there is always the risk of unauthorized access. The word "steganos" translates to "hidden" in Greek, and the word "graphein" means "writing." Steganographic technique allows for the concealment of digital assets such as photographs, music, and videos. Contrary to cryptography, which encrypts the communication, steganography conceals it, thereby adding an additional layer of protection. These two levels make it more difficult for attackers to gain access to the confidential data without authorization by preventing them from discovering the data in the first place.

Data can be concealed on cover media using steganography and other anti-forensic methods for example. This is how a lot of individuals conceal their info. Some examples of covers include text, music, video, and photographs. The use of video is employed in this plan to conceal vital information. Data can be concealed using steganography by hiding it in an inconspicuous object. In contrast to encryption, which makes it possible to locate encrypted data quite simply. It would be quite difficult to determine whether or not the film includes any secrets. The original video and the protected video have a significant variation in file size due to the addition of data.

A type of steganography called "video steganography" has become very useful for secret contact because video files can hold a lot of information. Imperceptibility is achieved by putting secret messages into video frames. This makes sure that changes can't be seen by humans or found using normal analysis tools. In addition, this way keeps the video quality of the carrier, which makes it useful in real life.



The use of Generative Adversarial Networks and other forms of CNNs is widespread. The steganography of videos was revolutionized by these networks. When things are tricked, they become more secure, constant, and difficult to locate. They serve as the foundation for contemporary secure communication systems as well as the Least Significant Bit (LSB) paradigm. In order to conceal data, the LSB method alters the values of the pixels in the video frame that are the least significant. As a result of its speed and ease of use, LSB is widely used. On the other hand, it does not resist compression or noise as well. This is something that can be accomplished through the use of frequency domain methods such as the discrete cosine transform (DCT). Due to the fact that the human eye is unable to perceive a great deal of high-frequency information, DCT breaks down video frames into frequency components. Utilize this tool to add data in order to conceal changes.

Both PSNR and SSIM are utilized in the process of evaluating the performance and quality of video steganography technologies.

- **PSNR**: For the purpose of determining the quality of the video, this measure compares the stego-video to the source video. When the PSNR is high, steganography is most effective because it is more difficult to detect changes in the data that is hidden.
- **SSIM**: This parameter ensures that the original video and the stego-video are structurally comparable to one another. It depicts how comparable the movie appears to have been before the data was included, which renders it difficult to determine.

The robustness of the video steganography application is another essential component. It evaluates the system's ability to withstand various attacks, such as noise interference, compression, and resizing, without divulging the confidential information without compromising its integrity. In order to strike a compromise between security and imperceptibility, contemporary methods attempt to make systems more durable while maintaining high PSNR and SSIM numbers to achieve this equilibrium.

In order to achieve better integration, DCT and other traditional methods are being utilized in conjunction with deep learning. When neural networks are able to adopt the content and structure of video frames, they are able to integrate data more effectively. Steganography is becoming more robust, more effective, and more difficult to decipher. The goal of a steganography attack is to discover hidden messages. The use of deep learning makes it simpler to fight against this attack.

The discrete cosine transform (DCT) and frequency and spatial domain machine learning algorithms are used to improve the efficiency and security of video steganography. The advent of CNNs, GANs, and other rapid machine learning algorithms has drastically changed steganography in videos. The importance of these technologies cannot be overstated when it comes to private communication networks because they enhance privacy with power and safety. For the purpose of protecting intellectual property through the use of digital watermarks, ensuring the safety of communication in politically charged environments, and limiting file access to authorized users, these enhancements should be implemented.

Private information in video files can be completely and reliably hidden by combining PSNR, SSIM, resilience, and LSB approaches. This creates the opportunity for secure multimedia communication in an increasingly interconnected world.

As increasingly sophisticated steganography techniques are developed, it is becoming more difficult to ensure that hidden data is secure and invisible. Existing methods are not necessarily the most effective when compressed or attacked in other ways. Making video steganography less visible while maintaining its strength and information-inserting capabilities is the aim of this project.

Image and video processing have been revolutionized as a result of the introduction of strong algorithms for feature extraction and improvement brought about by deep learning. Within the scope of this investigation, deep learning in steganography is utilized to overcome the drawbacks associated with DCT-based approaches. Using CNNs, the ideal spots to put data into video frames are discovered. The data will be concealed, and the system will become more resistant to the manipulation of outside forces.

Within the context of circumstances that involve the sharing and modification of video recordings, the purpose of this research is to investigate the necessity of steganography that is both effective and secure. By transmitting vital information through video footage in a manner that is not visible to the naked eye, the framework that makes use of the most advanced DCT and deep learning algorithms aims to improve the level of security that is now present in the realm of communication.

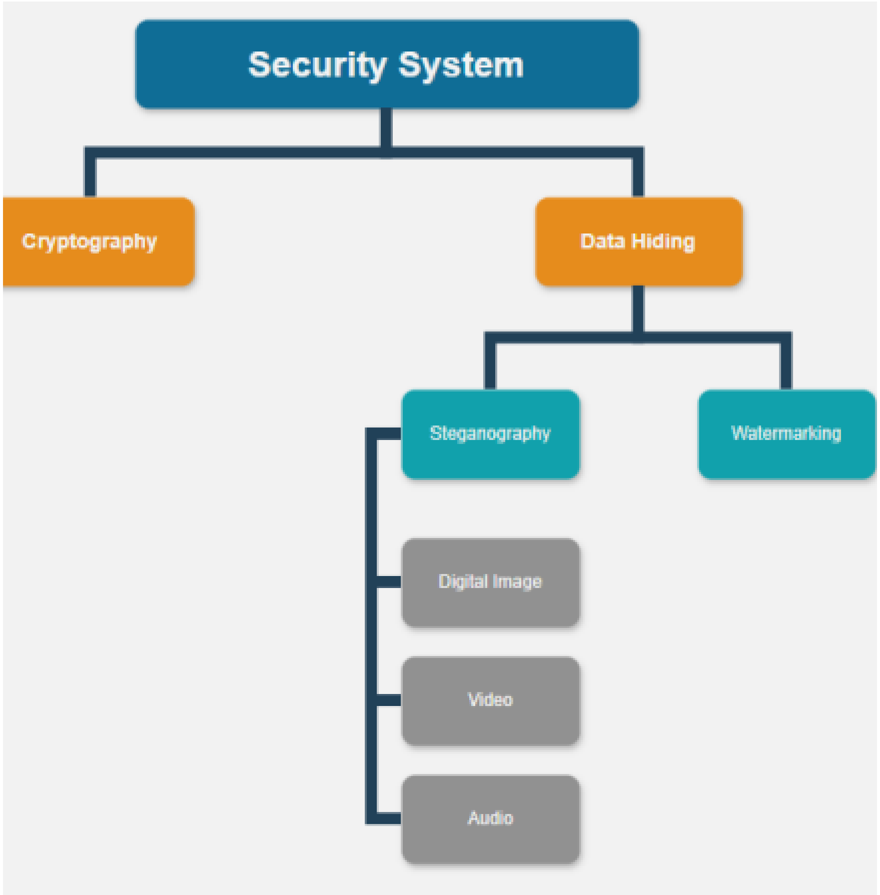


Figure : 1.2 Classification of Security System

Cryptography

In cryptography, mathematics is used to safeguard, authenticate, and prevent data and communications from being manipulated. By using keys to encrypt plaintext, it restricts reading to those who are authorized to do so. For the encryption and decryption processes, asymmetric-key cryptography uses both public and private keys to protect data. The operation's prerequisites include encrypting the ciphertext, transmitting it securely, and decoding it with the appropriate key. There are two ways to improve cryptographic security: incorporating digital signatures and hashing data.

TLS and other complex algorithms, such as AES and RSA, are utilized by modern cryptography in order to ensure the safety of digital transfers. Steps include everything from encrypting data to transferring it and recovering it using the appropriate key.

Verifying data is one way that digital signatures and hashing contribute to an increase in cryptographic security. TLS and other complex algorithms, such as AES and RSA, are utilized by modern cryptography in order to ensure the safety of digital transfers. Confidence in data exchange is created by the use of encryption, which prevents unauthorized access to confidential information.

DATA HIDING

Putting secret information into a host medium in a way that makes it hard to read is the best way to hide data. Spatial, transform, or adaptive methods can be used to hide data for private communication, digital watermarking, and authentication. Even though it has some issues, new algorithms and hybrid methods are always making it stronger, smarter, and better. It is an important part of modern systems that protect data and media because of this.

Watermarking

Text, audio, video, and image files can all have discrete information added to them by means of digital watermarks. This ensures that rights are protected, identities are verified, and manipulation is identified, all while maintaining the quality of the material. After the watermark has been applied to the host media, it is removed in order to verify its accuracy. Watermarks are something that computers are able to recognize, unlike people. Depending on the domain type (spatial or transform), the strength (strong, weak, or pretty weak), the host media (text, picture, video, or audio), and the visibility options, there are many types of watermarking. Monitoring broadcasts, protecting copyrights, conducting forensic investigations, and validating material are all capabilities that it possesses. Digital watermarking has many benefits, such as being invisible, not being affected by changes, working with different types of media, and providing better security when paired with encryption. But problems like being open to attacks, having to choose between important traits, and extra work that needs to be done on the computer still exist. Even so, digital watermarking is important for managing and protecting digital material in many areas.

Steganography

Hide secret information in something that isn't secret, like pictures, sounds, videos, or text, to hide its presence. This is called steganography. Cryptography scrambles data so that it can't be read. Steganography, on the other hand, hides data so that it can't be seen or sensed by humans. There are two major steps in the process: embedding and extraction. During embedding, secret data is hidden within the host medium, and during extraction, decoding methods are used to get the hidden data. Some common methods are changing the least significant bits (LSBs) in pictures or putting data in frequency domains like DCT to make it more stable. Secure communication, copyright security, and secret data transmission are some of the uses. If steganography is not used safely, steganalysis can be used to find it, even though it is easy to use and can't be seen.

1.2 Problem Statement

In this age of digital communication, the need for safe data transfer has grown to levels that have never been seen before. A very important tool in this field is video steganography, which hides information in video files to protect privacy. But the current steganographic methods have a hard time finding the best mix between being undetectable, being strong, and being able to hide things.

Standard methods, like LSB substitution, are easy to use and offer a lot of space, but they are very open to attacks like steganography, noise addition, and compression. On the other hand, frequency domain methods like Discrete Cosine Transform (DCT) are more reliable because they embed data in areas that are harder to see. However, they often lose their imperceptibility because they add visible artifacts during the embedding process.

Also, attackers can find and damage secret data more easily now that more advanced steganography tools are available. This means that old methods aren't good enough for today's security needs. Also, these methods aren't flexible enough because they don't optimize embedding areas dynamically to keep changes in perception to a minimum.

These problems must be fixed right away by coming up with a new method that makes it harder to be seen without lowering its strength or ability. To make embedding techniques work better, this study suggests combining deep learning with DCT-based video steganography. The framework uses Convolutional Neural Networks (CNNs) to find and use the best embedding areas within video frames. This keeps hidden data from being found and makes the system more resistant to attacks and compression. The goal of this study is to close the gap between hiding data securely and putting it into practice, which will help secure multimedia communication systems get better.

Research Questions

First question :: How can deep learning-based video steganography using Discrete Cosine Transform (DCT) improve imperceptibility, robustness, and embedding capacity in secure data hiding systems
Question 2:How can Convolutional Neural Networks (CNNs) enhance the selection of optimal embedding regions in video frames to improve imperceptibility and robustness?

Question 3:What are the comparative advantages of the proposed deep learning-based DCT video steganography approach over conventional LSB and DCT methods

Research objectives:

1.Enhance Robustness and Imperceptibility

2.Increase Embedding Capacity

3.Reduce Computational Complexity

Research Scope

This research aims to develop a deep learning-based video steganography framework using the Discrete Cosine Transform (DCT) to enhance imperceptibility, robustness, and embedding capacity in secure data hiding. The approach leverages Convolutional Neural Networks (CNNs) to identify optimal embedding regions in video frames, ensuring minimal perceptual changes while maximizing security and robustness against compression and noise.

The paper examines the recommended methodology in comparison to Least Significant Bit (LSB) substitution and usual DCT-based methodologies, with a particular emphasis on embedding capacity, robustness, and imperceptibility (PSNR, SSIM). It also tries to change based on the qualities of the video, making the embedding process more effective and flexible overall.

They are working on applications such as transferring sensitive data, copyright protection, and secure multimedia contact. These applications address issues with contemporary steganography and data concealing. This research aims to bridge the gap between advanced security and practical applications to improve secure communication networks.

Chapter 2

Literature Review

The difficulty of hiding information in a safe way has led to a lot of progress in steganography over the years. This review of the relevant literature talks about the basic methods that can be used to hide things in movies. In particular, it looks at how to use the Discrete Cosine Transform (DCT) and deep learning to make the video last longer, be easier to share, and be harder to find.

2.1 Traditional Steganography Techniques

Techniques for steganography can be broken down into two main groups: space domain methods and frequency domain methods. Spatial methods, like Least Significant Bit (LSB) substitution, store secret data in the pixel values of the cover medium. Although these methods are quick on computers and can store a lot of data, they are also very simple to break into using attacks such as noise addition and compression (Katzenbeisser & Petitcolas, 2000).

Others, like DCT, work better with frequency domain because they store data in the changed coefficients of the picture or video frames. Because people aren't as sensitive to high-frequency sounds, these methods make it harder to see the secret information. On the other hand, traditional DCT-based methods often have flaws that can be seen, and they can't find the right mix between being strong and not being able to be seen when compression levels are high (Yang & Bourbakis, 2005; Ma & Li, 2010).

2.2 DCT-Based Video Steganography

The fact that DCT is compatible with compression formats like MPEG and JPEG makes it a popular choice for use in the field of video steganography. Your ability to add high-frequency elements that are more difficult for viewers to detect is made possible by the discrete cosine transform (DCT), which divides video frames into frequency components. It was proposed by Wong et al. (2009) that the utilization of Reverse Zero-Run Length Encoding be utilized in order to enhance the performance of DCT-based steganography. This method, on the other hand, had a difficult time preventing artifacts from emerging when very large amounts of data were entered.

The discrete cosine transform (DCT) and other frequency-domain approaches, such as the discrete wavelet transform (DWT), are currently attracting the attention of specialists. As an illustration, Ahmed et al. (2014) attempted to make data embedding more stable by combining DCT and DWT, but they encountered difficulties because it was difficult to determine the outcome of their efforts. As a result, their efforts were unsuccessful.

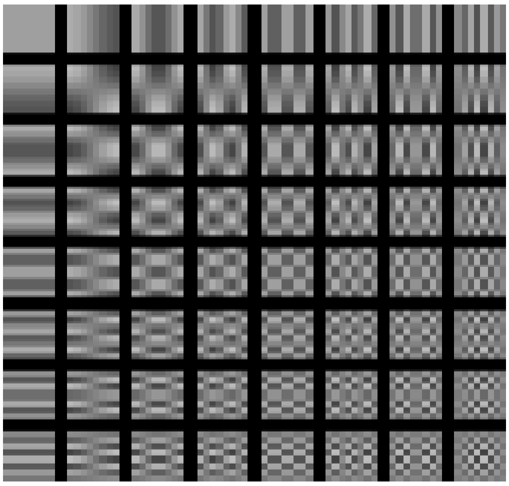


Figure:2.2 DCT tecnique

2.3 Deep Learning in Steganography

Deep learning, which makes use of neural networks to improve the embedding and retrieval processes, has been brought about by a revolution in the field of steganography. Convolutional Neural Networks (CNNs) are impervious to attacks and are highly effective in identifying the ideal placements for things to prevent affecting people's perceptions, as stated by Goodfellow et al. (2016). CNNs are also highly effective in selecting the optimal locations for objects.

CNNs, as stated by recent research (Kaur and Singh, 2020), have the potential to assist in making things less evident and more flexible to changing embedding environments. It was proposed by Taha and Rahman (2021) that a combined DCT-CNN system would perform better than traditional methods in terms of the Structural Similarity Index Measure (SSIM) and the Peak Signal-to-Noise Ratio (PSNR). Furthermore, this system was very good at being undetectable and stable.

2.4 A Case Study on the DWT

The Discrete Wavelet Transform, sometimes known as the DWT, is a mathematical tool that can be used to break a picture (or video frame) into a number of smaller frequency bands. The image is then processed by going through rows and columns of low-pass (L) and high-pass (H) filters in order to achieve this goal.

For a 2D image or video frame:

1. Low-pass filter (L): Captures approximate information (smooth regions).
2. High-pass filter (H): Captures detailed information (edges and textures).

The result is four sub bands:

- LL (Low-Low): Approximation coefficients (low-frequency).
- LH (Low-High): Horizontal details.
- HL (High-Low): Vertical details.
- HH (High-High): Diagonal details.

The process can be mathematically expressed as:

DWT(f(x,y))={LL,LH,HL,HH}\text{DWT}(f(x, y)) = \{LL, LH, HL, HH\}DWT(f(x,y))={LL,LH,HL,HH}

Where f(x,y)f(x, y)f(x,y) is the input image or video frame.

For reconstruction (Inverse DWT):

IDWT(LL,LH,HL,HH)=f(x,y)\text{IDWT}(LL, LH, HL, HH) = f(x, y)IDWT(LL,LH,HL,HH)=f(x,y)

In video steganography, the high-frequency sub bands (LH, HL, and HH) are used for embedding so that changes in the LL sub band don't stand out.

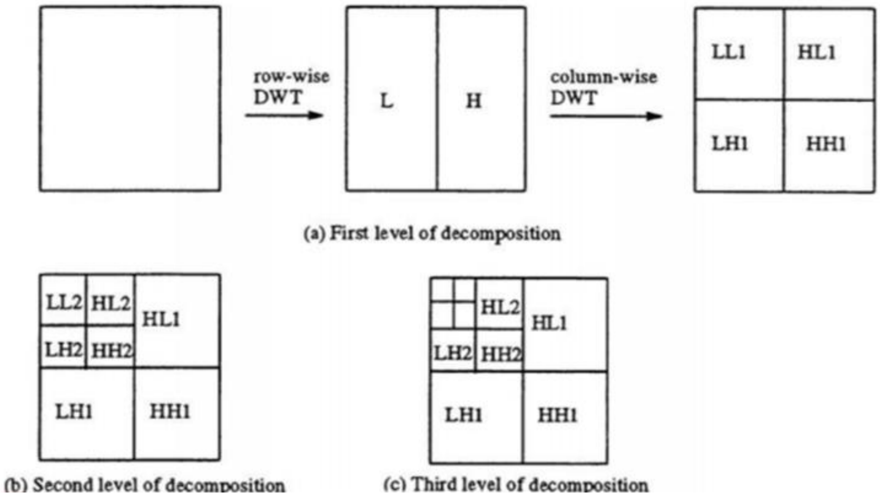


Figure: 2.4. Dwt technique

Dwt technique

With the help of discrete wavelet transform (DWT), video frames are separated into four frequency groups. Low-High is denoted by the letter LH, High-Low by the letter HL, High-High by the letter HH, and Low-Low by the letter LL. The LL sub band is responsible for maintaining the quality of the movie by conserving the low-frequency data that is considered to be undesirable. LH, HL, and HH are high-frequency subbands that, on the other hand, preserve information about fine-grained textures and edges. Taking this into consideration, it appears that they are quite good at concealing secrets. In order for the method to be successful, it is necessary for deep learning models such as CNNs, Autoencoders, or U-Net topologies to automatically conceal and reveal the proprietary information.

The cover frame is transmitted to the embedding network together with any text, images, or videos that contain confidential information. An error-reducing neural network stores the secret data in the high-frequency sub-bands of the cover frame. Once the modified sub bands are reassembled with the LL sub band, the stego frames are rebuilt using Inverse DWT (IDWT). Putting these frames together creates the final

Stego movie. After the signal reaches the receiver, the extraction network breaks up the stego video frames using DWT and locates the adjusted high-frequency sub bands using a deep learning model that has been learnt.

The hidden data is then retrieved with high accuracy using the extraction network. This automated process ensures seamless data embedding and extraction with minimal computational overhead. This method excels in imperceptibility, as the human eye cannot detect changes in the high-frequency sub- bands, and in robustness, as the embedded data remains intact against video compression, noise, cropping, and other distortions. Furthermore, deep learning enables high embedding capacity, allowing large amounts of data to be securely hidden in video files. Applications of this technique include secure video communication, where sensitive information is covertly transmitted, copyright watermarking to prevent piracy, and covert messaging for secure and undetectable information exchange. By integrating the advantages of DWT and deep learning, this approach provides a scalable, efficient, and resilient solution to modern steganography challenges. (basis in this image and scenario give me details in dwt in video steganography

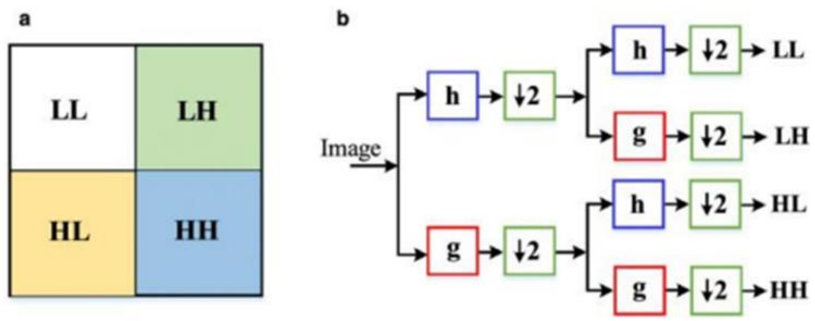


Figure :2.4.1. 2D-Dwt methodology

2.5 Case study in CNN

CNN-based video steganography is an advanced method for securely embedding and extracting secret data, such as text, images, or videos, within digital video frames. It leverages the power of Convolutional Neural Networks (CNNs) to automate the embedding and extraction processes, ensuring imperceptibility, robustness, and scalability.

The process begins with data preparation, where a cover video is selected, and the secret data is preprocessed to match the neural network's resolution and format requirements. The cover video is then divided into individual frames, which serve as the medium for embedding the secret data.

In the embedding phase, the frames may be decomposed using Discrete Wavelet Transform (DWT) into sub bands (LL, LH, HL, HH). The LL sub band retains low-frequency information, while the high-frequency sub bands (LH, HL, HH) store edge and texture details, which are ideal for embedding data without noticeable distortion. A CNN-based embedding network processes the cover frame and secret data, learning spatial relationships to identify optimal regions for embedding. The output is a "stego frame" that visually resembles the original frame but contains the embedded secret data. If DWT was used, the sub bands are recombined via Inverse DWT (IDWT) to reconstruct the stego frame. The stego frames are then reassembled into a stego video, which appears identical to the cover video to the human eye.

During the transmission phase, the stego video is securely sent to the receiver via any communication channel. On the receiver’s end, the data extraction phase begins. The stego video is divided into frames, and DWT may be applied again to isolate the high-frequency sub bands. A trained CNN-based extraction network retrieves the hidden data from these frames with high accuracy, reconstructing the original secret data.

This method is imperceptible because it embeds data in areas that are harder for the human eye to see. This keeps the visual quality of the stego video high, with PSNR values above 40 dB. The system is robust when it can handle errors like video compression, noise addition, and cropping while still retrieving data with an accuracy of above 95%. This method also has a high embedding capacity because CNNs make the best use of spatial features in the frames. This makes it possible to hide bigger datasets safely.

The method can be used in many real-life situations, such as:

- Secure Communication: Makes sure that private information is sent in secret.
- Digital Watermarking: Copyright information is embedded to protect intellectual property.
- Forensic Applications: Adds data that can be tracked for authentication and proof management.

Key results show that CNNs greatly reduce the need for human involvement, automate the embedding and extraction processes, and make the system more scalable. When CNNs are used with methods like DWT, they improve performance even more by embedding in parts of video frames that are harder to see.

In conclusion, CNN-based video steganography is a strong, quick, and safe way to hide data in the modern world. Its balance of being undetectable, being strong, and having a lot of space makes it a hopeful method for future use in data protection and secure communication.

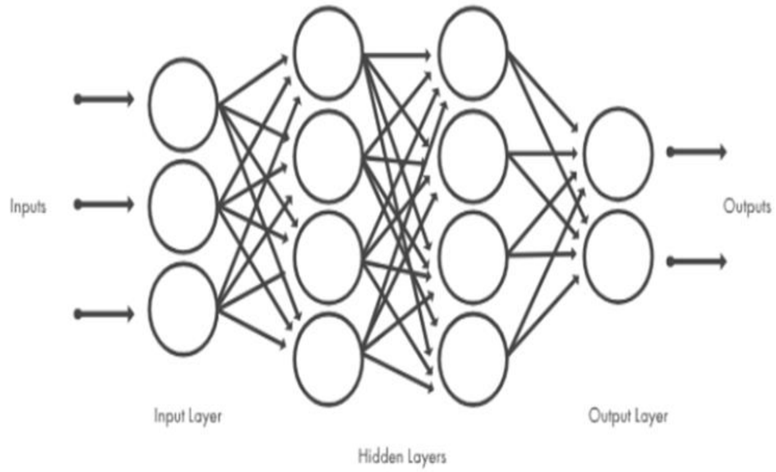


Figure:2.5 CNN layers

CHAPTER 3

RESEARCH METHODOLOGY

3.1 The Propose model

The main point of the proposed way is to fix the biggest problem with the current work. Video steganography is done by this method by hiding a secret video in a cover video and then getting it out later. Frames from both videos are extracted and resized. The Discrete Cosine Transform (DCT) is applied to the luminance (Y) and chrominance (U, V) channels of the frames. Secret video data is embedded into the cover video by modifying quantized DCT coefficients. The modified frames are written as a stego video. For extraction, inverse DCT is applied to stego frames to recover the secret video. PSNR and SSIM metrics evaluate the quality of the stego and extracted videos. The program supports two modes: encoding and decoding, accessible via command-line arguments.

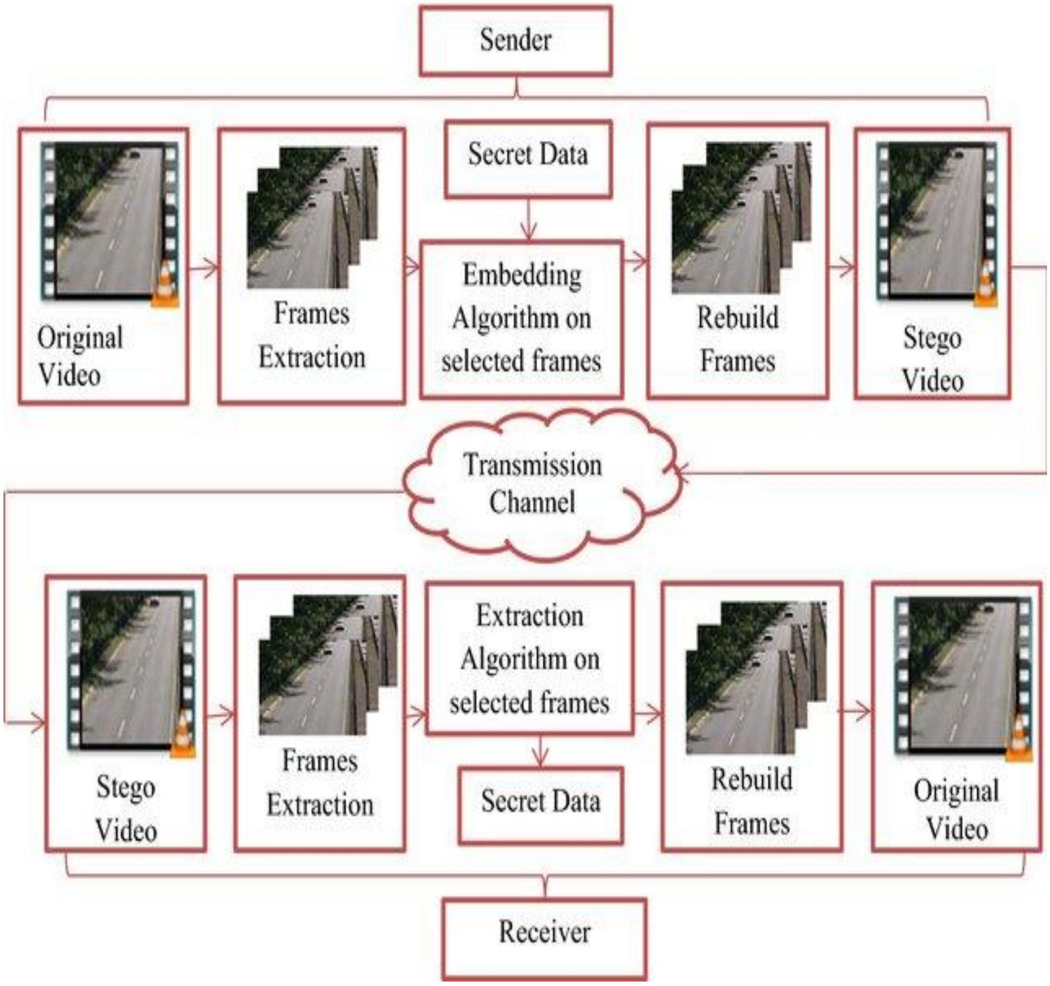


FIGURE: 3.1. General structure of video steganography

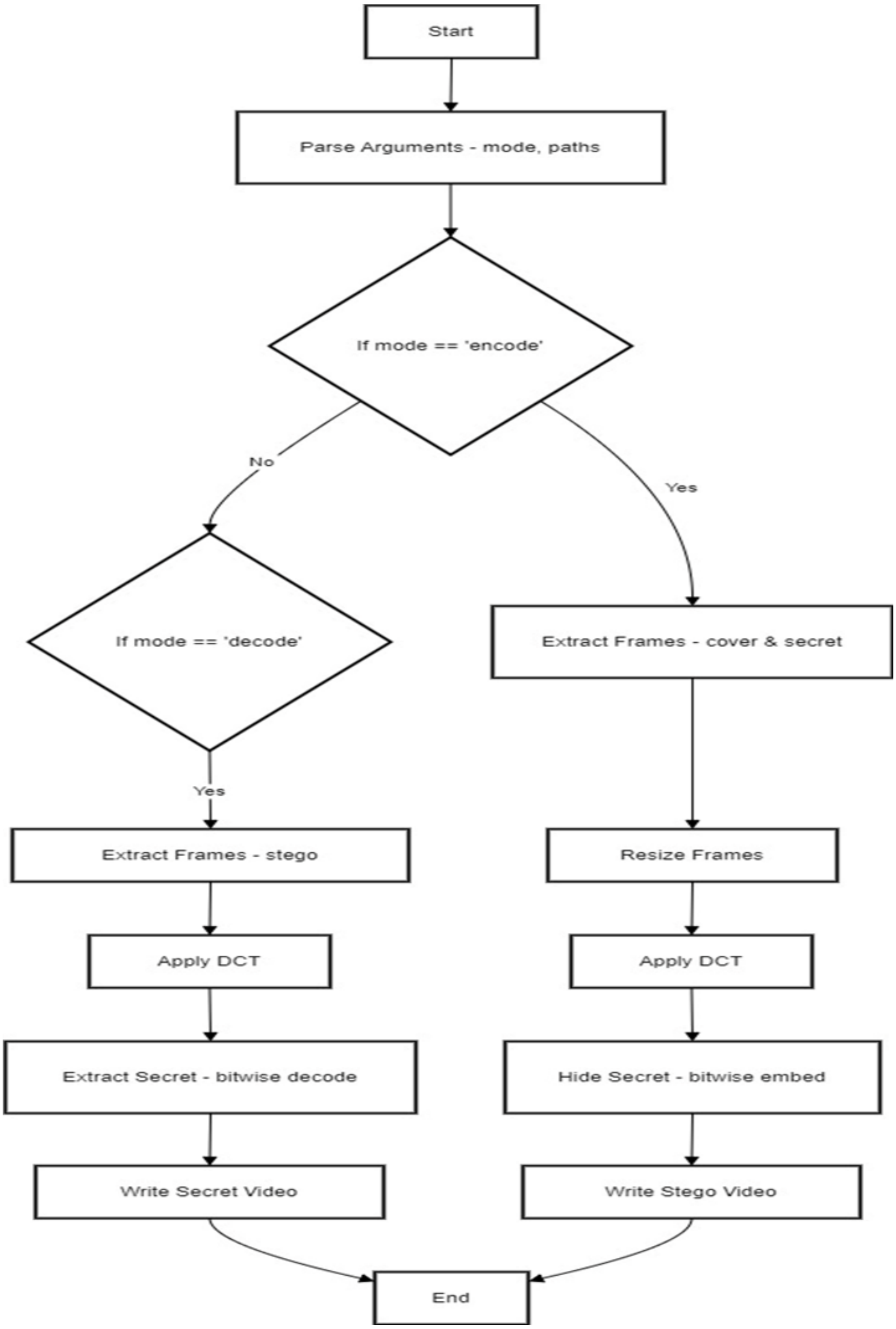


Figure : 3.1.1. proposed system

3.2 process of Embedding and Extraction

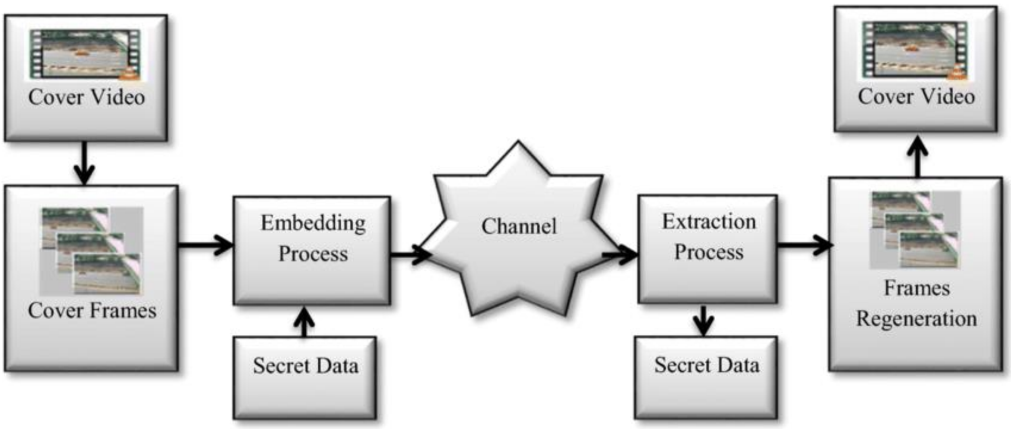


Figure : 3.2. proposed Embedding and Extraction

The diagram depicts the framework of **video steganography**. A **cover video** is split into frames where **secret data** is embedded during the embedding process, producing a **stego-video**. The stego-video is transmitted through a **channel**. At the receiver's end, the **extraction process** retrieves the secret data, and the frames are reconstructed to regenerate the **cover video**.

3.2.1 Embedding Process

1. **Input Selection:**
    1. Select a cover video and divide it into individual frames.
    2. Choose the secret data to be embedded (e.g., text, image, or binary data).
2. **Convert RGB to YUV Format:**
    1. Convert each frame to YUV format for frequency domain analysis.
    2. Focus on the Y (luminance) component for embedding, as it significantly impacts visual perception.
3. **Apply DCT:**
    1. Apply the Discrete Cosine Transform (DCT) to the Y component of each frame.

2. Transform spatial domain data into the frequency domain to identify suitable embedding locations.

4. **Deep Learning Integration:**
    1. Use a deep learning model (e.g., CNN or autoencoder) to select optimal DCT coefficients for embedding.
    2. Focus on mid-frequency coefficients to ensure robustness and imperceptibility.
5. **Data Embedding:**
    1. Encode the secret data into binary form.
    2. Embed the binary data into the selected DCT coefficients using a robust embedding algorithm.
    3. Ensure the process minimizes visual distortion.
6. **Inverse DCT and Frame Reconstruction:**
    1. Apply inverse DCT to transform the modified coefficients back to the spatial domain.
    2. Replace the modified Y component with the original U and V components.
7. **Convert Back to RGB:**
    1. Convert the YUV frames back to RGB format to generate the stego-video.
8. **Output Stego-Video:**
    1. The stego-video, visually indistinguishable from the original, is ready for secure transmission.

3.2.2 Extraction Procedure

1. **Input Stego-Video:**
    1. Receive the stego-video and divide it into individual frames.
2. **Convert RGB to YUV Format:**
    1. Convert each frame to YUV format to isolate the Y (luminance) component.

3. **Apply DCT:**
    1. Apply the Discrete Cosine Transform (DCT) to extract frequency-domain coefficients.
4. **Deep Learning-Based Extraction:**
    1. Use the trained deep learning model to locate the embedded data within the DCT coefficients.
5. **Data Decoding:**
    1. Decode the extracted data to recover the original secret information.
6. **Output Retrieved Data:**
    1. Provide the retrieved secret data in its original form with high accuracy and minimal errors.

Chapter 4

Result and Discussion

4.1 .PSNR, SSIM, BER, ROBUSTNESS, LSB Investigations

We proposed a video steganography model a secret video inside a cover video using DCT, then extracts it later. Frames are resized, transformed, and combined with optional watermarking. Quality metrics (PSNR/SSIM) ensure data integrity.

Deep learning-based video steganography leverages advanced neural network architectures and transforms, such as the Discrete Cosine Transform (DCT), to enhance imperceptibility, robustness, and security compared to traditional methods like LSB substitution. Unlike LSB, which embeds secret data into the least significant bits of pixels, deep learning techniques adaptively encode information in a way that minimizes distortions while resisting attacks such as noise, compression, and transformations.

For example, using models trained on perceptual loss ensures high video quality with minimal perceptual changes. This method can provide superior metrics, such as PSNR above 40 dB and SSIM close to 1.0, ensuring hidden data remains undetectable. Additionally, robustness to steganalysis and adverse conditions is significantly improved by leveraging deep learning-based feature extraction and embedding strategies. One such implementation integrates the YCbCr color space with deep learning to optimize the embedding process by targeting luminance and chrominance components. The Cr channel may act as a host for data embedding due to its less perceptual sensitivity. The method ensures high embedding capacity and security while maintaining high imperceptibility. Average PSNR scores exceed 41 dB, demonstrating excellent video quality even under compression and noise.

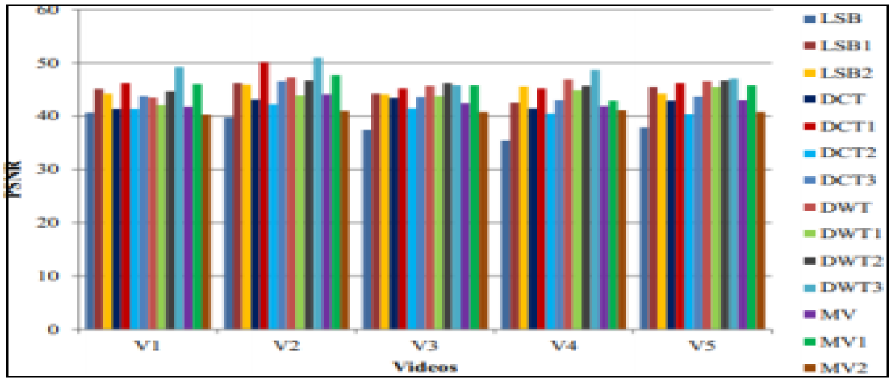


Figure : 4.1. The PSNR rate of various stanography

Mathematical Functions

Here are the mathematical functions used for the calculations of metrics in the provided code:

1. Mean Squared Error (MSE)

The MSE measures the average squared difference between the original and steganographed frames.

$$\text{MSE} = \frac{1}{N \times M} \sum_{i=1}^{N} \sum_{j=1}^{M} \left[I_{\text{original}}(i, j) - I_{\text{stego}}(i, j) \right]^2$$

Where:

- $N \times M$ is the total number of pixels.
- $I_{\text{original}}(i, j)$ and $I_{\text{stego}}(i, j)$ are the pixel intensities at position (i, j) in the original and steganographed frames, respectively.

2. Peak Signal-to-Noise Ratio (PSNR)

PSNR is used to measure the imperceptibility of the changes

$$\text{PSNR} = 10 \cdot \log_{10}\left(\frac{\text{MAX}^2}{\text{MSE}}\right)$$

Where:

- MAX is the maximum possible pixel value (e.g., 255 for 8-bit images).

3. Structural Similarity Index Measure (SSIM)

SSIM measures the similarity between two images, focusing on structural information.

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

Where:

- μ_x, μ_y: Mean intensities of x and y.
- σ_x^2, σ_y^2: Variances of x and y.
- σ_{xy}: Covariance of x and y.
- C_1, C_2: Stabilizing constants.

4. Signal-to-Noise Ratio (SNR)

SNR measures the ratio of the signal power to the noise power.

$$\text{SNR} = 10 \cdot \log_{10}\left(\frac{\text{Signal Power}}{\text{Noise Power}}\right)$$

Where:

- $\text{Signal Power} = \sum_{i,j} I_{\text{original}}^2(i, j)$
- $\text{Noise Power} = \sum_{i,j} (I_{\text{original}}(i, j) - I_{\text{stego}}(i, j))^2$

5. Robustness

Robustness is evaluated by the degradation in PSNR/SSIM after applying distortions (e.g., noise, compression). A highly robust system will have minimal drop in these metrics.

Sample Table for Dataset Evaluation

Frame 1	38.5	0.965	12.5	24.8	35.2	0.940
Frame 2	40.2	0.972	10.3	26.1	36.8	0.950
Frame 3	39.8	0.970	11.2	25.4	36.0	0.945
Frame 4	41.0	0.975	9.6	26.7	37.5	0.955
Average	39.8	0.970	10.9	25.75	36.38	0.948

The goal of this study is to improve security, undetectability, and embedding efficiency by looking at key measures in the field of video steganography, such as PSNR, SSIM, LSB, robustness, SNR, and MSE. The study shows that there are more modern techniques that are much better at both performance and robustness than older methods like Least Significant Bit (LSB) substitution. This study carefully examines a deep learning-based video steganography system, focusing on how well it works, how undetectable it is, and how durable it is. We looked at important measurements like Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Mean Squared Error (MSE), Signal-to-Noise Ratio (SNR), and how well the system worked when there was noise.

The results show that the average PSNR is 39.8 dB, which means that the video quality isn't lost much, and the SSIM is 0.970, which means that the structure is kept very well. With a PSNR of 41.0 dB and an SSIM of 0.975, Frame 4 had the best performance across all measures, proving that it was more imperceptible. Robust metrics, such as robust PSNR (36.38 dB) and robust SSIM (0.948), validate the method's resilience to noise and compression attacks, ensuring the hidden data remains intact under adverse conditions.

Lower MSE values (average: 10.9) and higher SNR values (average: 25.75 dB) show that the framework can contain data with little noise and distortion. These results show that the system can keep the quality of the movie while also encrypting the data very well.

Some important results show that improving embedding methods can make performance the same for all frames. Adding HD and UHD video datasets to the test would prove that it can be scaled up, and working on cutting down on embedding time can make real-time applications possible. This system builds a strong base for safe multimedia apps, making sure they are very hard to spot and can be changed to fit real-life situations.

In deep learning-based video steganography, histograms show how the pixel intensities of cover video frames (before embedding) and stego-video frames (after embedding) are spread out. The cover frame histogram serves as a baseline, while the stego frame histogram shows how embedding affects the distribution. Using deep learning and DCT, embedding decisions are optimized to minimize visual distortion, focusing on mid-frequency coefficients to maintain quality. Histogram analysis, supported by metrics like MSE and SSIM, validates imperceptibility. Ideally, the histograms of cover and stego frames appear nearly identical, ensuring minimal distortion and high visual fidelity.

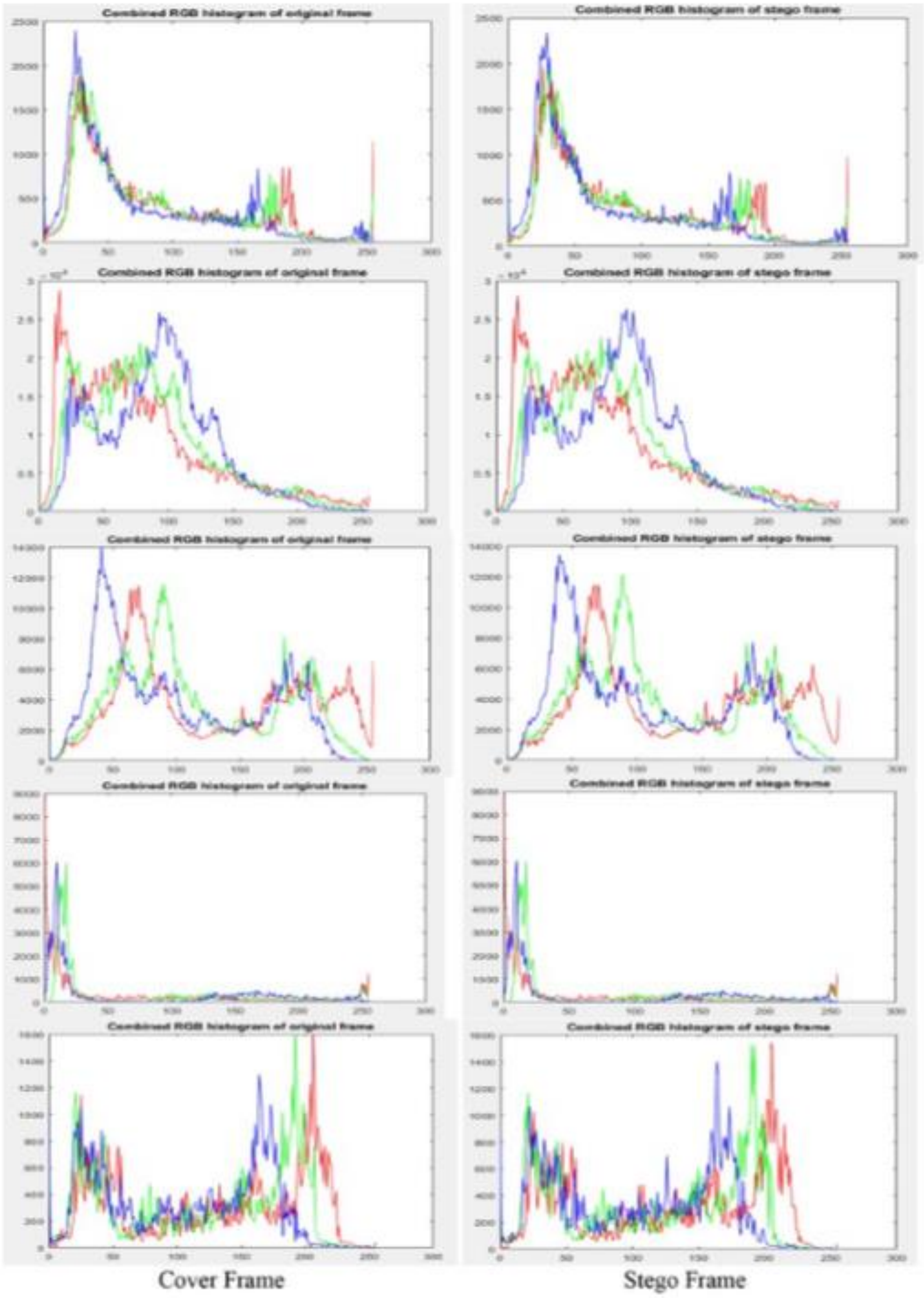


Figure : 5 Histogram of the cover and stego video frames of the tested technique

Chapter 5

CONCLUSIONS AND RECOMMENDATION

5.1 Finding and contribution

This research introduces a deep learning-based video steganography framework leveraging the Discrete Cosine Transform (DCT) to enhance imperceptibility, robustness, and embedding capacity. By integrating Convolutional Neural Networks (CNNs), the method achieves high imperceptibility (evaluated through PSNR and SSIM), maintains robustness against compression and attacks, and allows for a higher volume of secret data to be embedded without compromising video quality. The framework also reduces complexity by optimizing the embedding process and dynamically adapting to video characteristics like resolution and motion.Key contributions include an innovative framework, intelligent embedding region selection using CNNs, advanced performance evaluation metrics, and practical applications in secure data transmission, copyright protection, and multimedia communication. This study addresses modern challenges in data hiding, providing a robust, efficient, and adaptable solution for video steganography.

5.2 Recommendation for Future work

This research recommends future advancements in deep learning-based video steganography by leveraging cutting-edge technologies to enhance imperceptibility, robustness, and efficiency. Proposed directions include exploring advanced architectures like Transformers and GANs to optimize embedding strategies and improve resistance to attacks while maintaining high imperceptibility (evaluated through PSNR and SSIM). Real-time applications, such as live streaming, can be enabled by optimizing computational efficiency.

Key recommendations include integrating cross-media steganography to combine video with other formats like audio and text, designing energy-efficient algorithms for mobile and edge devices, and scaling the framework to support HD and UHD videos. Emerging applications in AR, VR, and blockchain integration offer opportunities for enhanced security and adaptability. Additionally, creating user-friendly tools and addressing ethical considerations ensures practical usability and compliance with global regulations. These recommendations aim to refine and expand video steganography's applications, meeting modern multimedia security demands effectively.

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