International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

GAN-Powered Image Steganography: Combining NLP and Generative Adversarial Networks for Text and Voice Encryption

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Abstract

Security and privacy are essential in modern times particularly given the volume of private data that is shared between platforms. Conventional encryption methods frequently fall short in protecting many data kinds, including text, speech and graphics. By integrating Generative Adversarial Networks (GANs) and Natural Language Processing (NLP) a novel approach is put forth for creating an advanced image steganography system that integrates text and audio encryption. The project trains the GAN model using the ImageNet dataset which includes an extensive set of photos and labels. In the GAN architecture the autoencoder encodes images and the decoder reconstructs them. The pixel-wise error per pixel is 35.96 for S-error and 30.55 for C-error. By encoding hidden text into photographs this creative method makes image steganography more effective while masking the information from view. For text encryption news data is used to train a T5 model that is driven by NLP approaches. A user-friendly interface designed with streamlit is part of the solution which enables users to upload photos for encryption and enter text using speech recognition or typing.

Keywords – Autoencoder, Encryption, Generative Adversarial Networks, ImageNet, Image Steganography, NLP, Speech Recognition and T5 Model.

1. INTRODUCTION

Since the number of internet users is growing quickly, data sharing is common and cyberattacks are becoming more frequent protecting private information has become a top priority in the digital age [1]. Conventional encryption methods such symmetrical and asymmetric encryption provide safe means of protecting data but they frequently fail when handling huge quantities of data or a variety of data kinds including text, voice and images. Security, integrity and reliability are crucial in a variety of industries, including online shopping, social networking sites, healthcare and government services. Furthermore, novel approaches to improve encryption of data and steganography have emerged as a result of developments in machine neural networks and artificial intelligence (AI). Combining Generative adversarial networks and Natural Language Processing or NLP to improve security through image steganography which enables secret information to be hidden within text and images is one such creative method. In order to create a dual-mode cryptography system capable of both picture and text encryption, the project described here combines GANs with NLP approaches [2]. We train an algorithm called GAN that can encode private data (like text) into images, guaranteeing privacy using the ImageNet data set which is a wide range of labelled images. In order to increase the effectiveness of encryption, we also use NLP techniques like tokenization on text and a T5 model for summarizing massive text data. The autoencoder used by the GAN architecture for encoding aids in hiding the encrypted data inside an image [3]. Text encryption involves transforming the data into an encrypted format using the T5 model which can subsequently be incorporated into the picture. Additionally, the system has dual input modes that let users to provide data for encryption using either speech recognition or text input. The system enables users to input photos for decoding after the encryption procedure is finished which allows them to recover the encoded text or audio content. This technology ensures security across many data formats by crossing the gap between picture, text and speech encryption [4].

With thousands of occurrences recorded annually hacking and data loss are becoming more prevalent worldwide. The 2023 Verizon Data Breach Investigations Report (DBIR) states that there were more than 2,000 verified hacking incidents globally exposing sensitive and personal information belonging to millions of people [5]. Strong encryption techniques are crucial since these incidents frequently comprise the loss of financial information, personal data and login passwords. Modern steganography like the one suggested in this study is increasing in popularity as a means of hiding data within digital media and images in addition to traditional encryption methods. According to a Markets and Markets analysis the global steganography market is projected to expand at an annual growth rate of 9.9%, from USD 1.3 billion in 2020 to USD 2.1 billion by 2025. This increase demonstrates the rising need for innovative data security methods in a number of industries such as communications, healthcare and finance. Cybersecurity issues are just as serious in India. The increasing ability to cyber threats is shown by the 1.16 million cyber events recorded by the Indian Computer Emergency Response Team in 2020 alone. Data security has become major issues as more individuals use social media services delivered via the cloud and online transactions. In response the Indian government enforced data security laws with measures like the Personal Data Protection Bill (PDPB) [6].

Objectives:

- Developing a solution for dual-mode encoding of text, image, and audio data that combines GANs and NLP approaches.
- For effective visual steganography and text encoding, train a GAN model using the ImageNet dataset.
- To optimize security of information in text format, use a T5 model for summarizing lengthy text inputs.
- Create a simple encoding and decoding interface with streamlit that supports text input and speech recognition.
- Achieve a strong encryption system with low pixel error to guarantee secure data recovery and excellent visual steganography.

2. LITERATURE SURVEY

The merging of steganography, encoding and machine learning has been examined in a number of earlier studies highlighting the ability of Generative Adversarial Networks (GANs) to improve data security. The least significant bits (LSB) of a picture were usually used to conceal hidden information in early visual steganography techniques although these techniques frequently reduced image quality and were prone to discovery. Convolutional Neural Networks (CNNs) and auto encoders are two deep learning approaches that are gaining popular over time due to their capacity to learn complex structures and perform more effective data embedding. In recent years GANs have been used to greatly increase the quality of encoding pictures making it more difficult to find hidden information because of their capacity to produce actual pictures through competitive learning. Li et al. although modern GAN-based systems frequently use linear convolutional neural networks which results in low hidden performance steganography is used for hidden communication with multimedia content. This problem is solved by building several communication channels between the expansion and contraction paths in a novel GAN-based spatial steganographic system [7]. According to experimental data this system performs better in terms of anti-steganalysis than current GAN-based schemes. Yuan et al. by using convolution neural networks have advanced image steganography has become more secure. A complete strategy based on generative adversarial networks (GAN) is put out to counter this [8]. Attack, Encoder, Decoder and Critical are the four modules that make up the scheme. Liu et al. proposed a notable development in machine learning and natural language processing especially in image steganography, is the Generative Adversarial Network (GAN) [9].

In the meantime, the field of Natural Language Processing (NLP) has made major contributions to encryption techniques especially when it comes to text data. The capacity of models like BERT, GPT and T5 to understand summarize and produce text across a variety of fields has led to their widespread use. For example, research has shown that transformer-based models such as T5 can be improved for text summary [10]. This can help in compressing vast amounts of data prior to encryption, improving security and efficiency. The use of NLP in encryption systems has also been enhanced by the introduction of speech recognition technologies which allow users to safely provide voice data for processing. This proposed work is a novel combination of visual steganography and NLP methods for dual-mode encryption where the summary and encryption features of advanced NLP models are combined with the advantages of GANs in image data security. More complex and adaptable encryption algorithms that address current security issues have been made possible by earlier research but the combination of text and image encryption is still a relatively new field of study. Hanif et al. proposed the Text-to-Text Transfer Transformer (T5) approach [11] an AI tool that can rapidly understand and summarize lengthy research papers is the subject of the study. Expert summaries and a variety of research publications were used to train the T5 model. It fared better than other models like BERT, GPT-2 and BART and received high scores in a number of metrics, such as ROUGE and BLEU. This study demonstrates how AI, and specifically the T5 model can cut down on the amount of time needed for comprehension and reading complex studies. Borah et al. examines and evaluates the T5 Transformer model's performance on the CNNDM, MSMO and XSUM datasets for abstractive text summary [12].

Demerits:

- Conventional steganography methods frequently produce visible visual error which leaves submerged data open to detection.
- The processing demands of CNN-based steganography techniques can make them difficult for real-time applications.
- Certain visual encryption methods have scalability issues and are ineffective when dealing with big datasets.
- Because of their lack of adaptability, early NLP encryption algorithms frequently generated text encryption that was poor or readily accessible.

3. DATA COLLECTION & PREPROCESSING

The ImageNet dataset a popular and highly diverse collection of images and labels that is used as a standard for numerous applications involving computer vision is the main source of data used in this work [13]. The dataset is perfect to develop a GAN-based steganography of images system because it includes millions of labelled photos in hundreds of categories. The model is trained for a number of tasks including encoding and decoding data using the labels that follow each image in the dataset. Because of the dimension and quality of the photographs in ImageNet preprocessing is a crucial step in improving the images for the model. The images are resized to uniform 64x64 pixel size to provide unity across the entire collection. This resizing reduces computational cost while ensuring that the model can precisely evaluate the images during reasoning and training [14]. To guarantee the accuracy and uniformity of the dataset a variety of preprocessing techniques are applied in addition to resizing. Normalization is one of the most important preprocessing steps. It involves reducing pixel values to a particular range, typically between 0 and 1. In addition to decreasing the likelihood of vanishing gradients or explosion which may affect model performance aids in the model's rapid convergence during training. Additionally, by ensuring that all pixel values are handled equally normalization stops some features from taking the spotlight because of their greater sc+ale. Furthermore, the dataset is artificially expanded and difficulty is introduced through the use of image augmentation techniques like motion, flipping and random cropping [15].

Min Max Scaling is used to increase the reliability of deep learning algorithms by scaling picture pixel values to a predetermined range usually [0,1] or [−1,1].

$$\mathrm{X}' = \frac{\mathrm{X} - \mathrm{X}_{\min}}{\mathrm{X}_{\max} - \mathrm{X}_{\min}}$$

Where, X is the original pixel value. $\mathrm{X}_{\min}$ and $\mathrm{X}_{\max}$ are the minimum and maximum pixel values in the image. X' is the normalized pixel value in the range [0,1] or[−1,1] (if scaled differently).

Following preprocessing the photos are divided into datasets for testing, validation and training. While the model is being tested on unseen data to assess its capacity for generalization this division guarantees that the model is interacting with a wide variety of data all through training. The model learns the connection between the data being encoded and the visual representations from the training dataset. To avoid overfitting the validation set is used to adjust hyperparameters and track the model's performance during training [16]. To make sure the model works as expected on untested photos a test dataset is set aside for the last assessment. Additionally, the photos are marked by labels that may include textual information that must be secured which increases the complexity and depth of data. News data is gathered from verified sources and placed through comparable preprocessing procedures for the work's NLP aspect. The use of tokens is used to divide the text data into smaller portions like words or sub words once unnecessary letters, punctuation and stop words have been eliminated. In order to convert textual information into a format that machine learning models can process tokens is necessary. In order to prevent the model from treating multiple versions of the same word as separate individuals, stemming or lemmatization is also done to reduce words to their base forms [17]. By decreasing the vocabulary size this preprocessing step enhances the model's accuracy and efficiency.

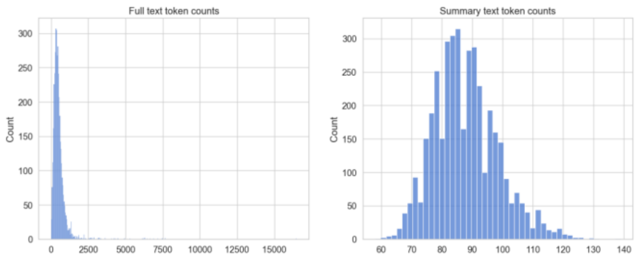

Fig.1 Full Text vs Summary Text Tokens Count

Following tokenization embedding techniques are used to further process the text by transforming it into numerical representations. The text must be represented as a collection of integers according to the T5 model employed in this study with each word or token (as shown in Fig.1) being mapped to a distinct vector in a vector space [18]. In order for the model to read and evaluate the text in a way that is readable by machines this phase is crucial. The text can be fed into the framework for encrypting or summary after it has been tokenized and embedded. This work's integration of text-based and based on pictures data processing enables smooth encoding and decoding with the model effectively handling both text-based encryption and visual steganography. For both text and image data the preparation stage guarantees that the input is uniform, clean and prepared for encoding. It improves the data to meet the unique requirements of the T5 and GAN models. Normalization and reducing images to 64x64 pixels simplify processing and guarantee that the algorithm can learn efficiently without being limited by unnecessary complications [19].

4. PROPOSED METHODOLOGY

The suggested methodology for this work combines modern techniques from Natural Language Processing (NLP) and Generative Adversarial Networks (GANs) to produce a strong encrypting system that can securely encode and decode text, image and audio data. Training a GAN model employing the ImageNet dataset is the first step in the technique. To ensure that the photos in this dataset are in a format that is appropriate for model training they are preprocessed by scaling them to 64x64 pixels and normalizing their pixel values. A discriminator and a generator make up the GAN architecture. While the discriminator tries to distinguish between the original and modified images the generator is in charge of producing visuals that possibly include secret details. In this study the input image is transformed into a lower-dimension pixels and then decode back into its original form using an autoencoder architecture. The fundamental benefit of employing this technique is that it preserves the image quality while allowing the hidden message to be placed within the picture in a way that is invisible to the human eye.

The proposed approach uses NLP techniques for managing text and speech data encryption in addition to the picture steganography system. The approach uses a T5 model a cutting-edge transformer model to handle and encrypt text data. To get the text ready for the T5 model it is initially processed using methods including tokens, stemming and embedding. After processing the text, the T5 model creates an encrypted copy of the input which is subsequently hidden inside a GAN model-generated image. The T5 model is also used for summarization if the input text is too lengthy. This reduces the text before encryption which improves the security measures and transmission procedures. Voice data can be entered by users using speech recognition technology that is integrated into the system. The voice input is converted into text by the system via conversion and the text is subsequently encrypted similarly to typed text. Dual-mode input is made possible via the streamlit-developed user interface which lets users talk or type straight into the device.

5. GENERATIVE ADVERSARIAL NETWORKS

The GAN-based autoencoder model utilized in this study combines the benefits of autoencoder architectures and Generative Adversarial Networks (GANs) to offer an effective approach for image steganography data encryption [20]. The generator and discriminator neural networks which make up GANs are trained in an adverse manner. The generator's goal is to produce data that is identical to real information while the discriminator's job is to differentiate between the generated and real data. The autoencoder is perfect for hiding encrypted information in an image since its encoder component compressed the image into its latent form and its decoder reconstructs it. Since it aids in developing a successful representation of the source data the autoencoder framework is especially ideal for this purpose (as shown in Fig.2). This enables the model to conceal encoded signals without significantly changing the appearance of the image. In order to integrate the hidden information (text) the encoder converts the initial image into a space with fewer dimensions. Following encoding, the image is reconstructed to its original dimensions by the decoder using the latent space representation [21].

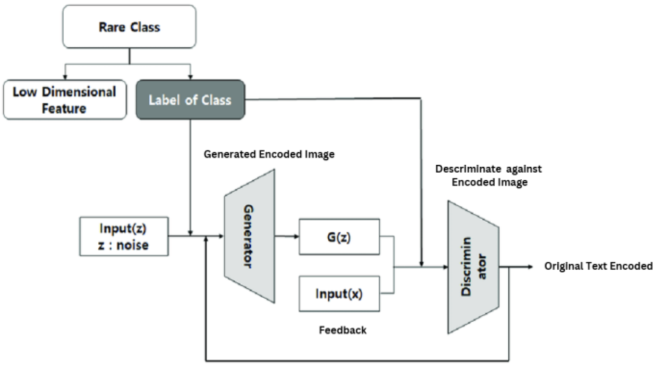

Fig.2 GAN Architecture

The ImageNet dataset which offers a comprehensive collection of images covering multiple categories and featuring a variety of objects is utilized for training the GAN-based automatic encoder model. Prior to normalization which involves scaling the pixel values between 0 and 1 these photos have been processed by being resized to 64 by 64 pixels. These preprocessed images are fed into the model during the training process when the discriminator learns to distinguish between the generated encoded images and actual photos from the dataset and the generator learns to create excellent encoded images by encoding secret messages. The generator is required by the adversarial training process to create realistic-looking images while simultaneously hiding the secret information in a way that the discriminator cannot see. The responsibility of translating the input picture into a lower-dimensional latent area falls to the encoder portion of the autoencoder in this study. This latent space model contains the hidden information which may be speech or text data. This encoding method is perfect for steganographic applications where reducing picture damage is essential since it guarantees that the initial image is compressed while concurrently inserting the secret data. The original content can then be recovered when the decoder uses this compressed latent form to rebuild the image. Pixel wise errors such as S-error (Sum of errors per pixel) and C-error (Cumulative error per pixel) are used to assess the quality of the reconstructed image [22].

Using an autoencoder in combination with GANs includes multiple benefits one of which is the capacity to learn effective data representations without the need for manual feature extraction. In order to integrate the secret data the autoencoder trains to extract the most significant features from the image and compression them into a latent space. Because the model can automatically extract relevant characteristics from the picture data it can operate more effectively and requires less manual involvement during the preparation steps. Furthermore, by reducing the possibility of losing information during compression as well the autoencoder's architecture makes sure that the encoded image maintains a visual quality that is comparable to the original. The ability of the model is also enhanced by GANs' adversarial character. The adversarial training procedure improves the generator's capacity to produce realistic images that can withstand the discriminator's examination [23]. This forces the generator to keep becoming better producing encoded pictures that get harder to distinguish from actual images. Conversely the discriminator gains the ability to distinguish minute variations between produced and genuine images. This enhances the model's overall quality leading to more realistic encoded images and more secure encryption.

The GAN-based autoencoder model's overall architecture aims to strike a balance between image quality and encryption. In order to contain the hidden message while maintaining the image's optical integrity the generator must produce an image that closely matches the original. While the autoencoder's compression guarantees that the hidden data is safely integrated without apparent error adversarial training guarantees that the resulting images are realistic. When these two methods are combined a powerful tool for safe data transfer is created allowing private information to be hidden within pictures and protected from strangers. By combining the advantages of GANs with autoencoders the GAN based automatic encoder model employed in this work offers an advanced form of image steganography that produces a highly safe and efficient encryption system. The model can produce high quality encoded images that hide secret messages without causing visible alterations by utilizing the strength of adversarial learning.

6. TEXT-TO-TEXT TRANSFER TRANSFORMER

Google Research created the highly strong and adaptable T5 model (Text-to-Text Transfer Transformer) which is designed to manage a variety of natural language processing (NLP) activities within a single

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framework [24]. To turn lengthy or complex texts into succinct summaries the T5 model is applied to text summary in this work particularly on news data. The transformer architecture on which the model is built is known for its outstanding performance in natural language processing tasks because of focus mechanism which enables it to assign varying weights to various input text elements based on their relative importance (as shown in Fig.3). Since both the input and the output are seen as text sequences T5 works on the premise that all NLP jobs can be framed as text-to-text problems. Data preparation is the initial step in the process of using the T5 model for news information summary. Ads, formatting mistakes and recurrent data are among the useless or noisy material that has been thoroughly removed from the news dataset.

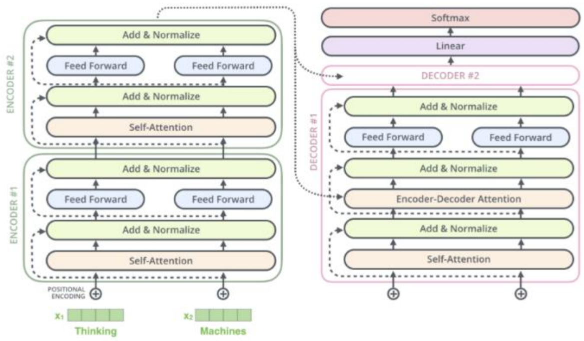

Fig.3 T5 Transformer Architecture

The preprocessed news data is used to improve the T5 model's performance for text summary. In order to improve the model and make it produce more precise and contextually relevant summaries it is necessary to train the model on a domain- particular dataset. To make sure it gets the main ideas and essential details from each article the T5 model is specifically adjusted for news items in this study. Because news stories frequently employ complicated vocabulary, abbreviations and a range of sentence patterns this stage is essential because it enables the model to adjust to their particular language and structure. In this study the text is optimized prior to encryption by using the summary capabilities of the T5 model. The length and complexity of the text can have an impact on the encoding procedure's efficiency because the encryption process uses the GAN-based autoencoder model to embed the text into images. Long or verbose inputs are condensed into short representations by employing T5 to summarize the text which facilitates their encoding and hiding within an image [25].

7. RESULTS

A number of visualizations that demonstrate the models, effectiveness in terms of both image quality and encryption efficiency are used to visually display the outcomes of the suggested GAN-based autoencoder model and T5 model for text summarization and encryption. Plots of the pixel-wise errors for the GAN-based autoencoder such as S-error (Sum of Errors per Pixel) and C-error (Cumulative Error per Pixel) show how effectively the model conceals the hidden data in the image while preserving the image's visual integrity. A quantitative evaluation of the amount of modification the encoded images receive during training is given by the S-error and C-error values lower values denote better performance (as shown in Fig.4). Evaluation criteria like ROUGE and BLEU scores which are plotted to show the quality of the text summarization similarly show the performance of the T5 model. The more accurate and appropriate to the context the summaries the greater the ROUGE and BLEU scores. By keeping the crucial significance of the original text unaffected and eliminating unnecessary data these metrics help in evaluating how successfully the model recovers more significant information.

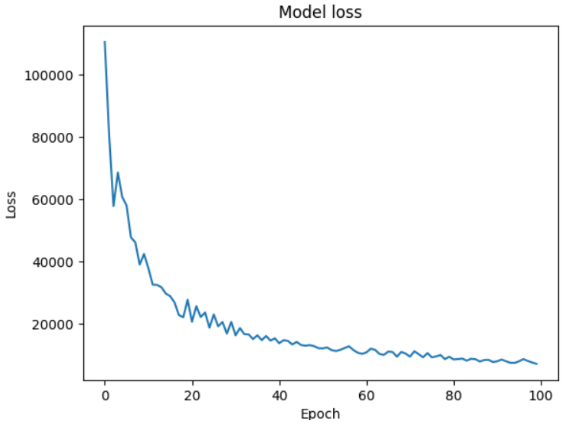

Fig.4 GAN Model Loss vs Epochs

The suggested system's user-friendly streamlit-built interface enables seamless encoding and decoding activities at real-time usage. Users are first given the option to enter text or speech data to begin the encoding process. The technology automatically summarizes longer text passages using the T5 model before encoding them into a picture. Users can either type the text or upload a document. Speech recognition software transforms voice input into text which is further processed in a similar manner. Following preparation, the data is encoded into a 64x64 pixel image by the GAN-based autoencoder model which essentially conceals the encrypted message inside the image. The user sees the encoded image and has the option to download or distribute it. The procedure is equally simple for decoding. The system uses the GAN-based automatic encoder model to decode the encoded image when the user uploads it. The original message is recovered with the least amount of damage possible thanks to the decoder, which takes the speech or hidden text data out of the picture.

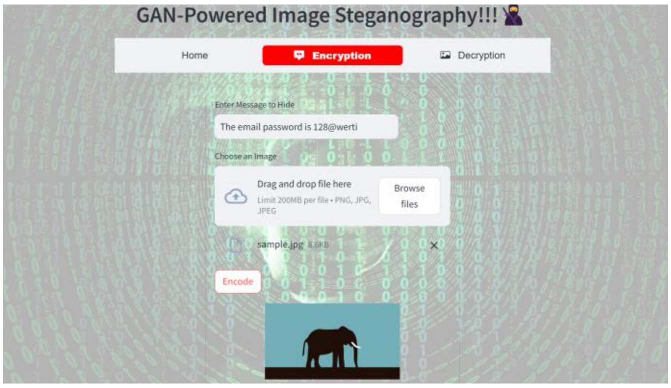

Fig.6 User Interface Encryption

Fig.7 User Interface Decryption

The system can handle a wide range of inputs such as lengthy news articles or audio data and produce encrypted outcomes in the form of encoded images (as shown in Fig.6 & 7) that may be safely exchanged during real time data encryption and decryption. The T5 model effective preprocessing and summarization procedures significantly cut down on the encryption time while guaranteeing that the system can easily handle both short and long inputs. The system swiftly recovers the encoded data and displays it in a legible format throughout the decryption process which is equally effective. The system's real-time nature makes it appropriate for applications like voice-based encryption for privacy, secure messaging platforms and private data sharing that demand quick and secure data transfer.

8. CONCLUSION

This research offers a very effective and safe way to encrypt data in a variety of formats such as text, images and speech by combining GAN-based autoencoders with T5 models for text summarization. The system successfully encodes secret data into images in a way that is both hidden and invisible to the human eye by using competitive learning and autoencoding techniques. This ensures that private data is kept hidden while maintaining the image's visually reliability. The T5 model is essential for reducing lengthy or complex textual material, improving encryption and increasing the system's capacity to process big inputs effectively. Users may securely encrypt and decode data in the form of text, images or voice with ease thanks to the actual time encoding and decoding features and a simple UI powered by streamlit. This creative method not only improves data security and privacy but also provides flexibility in practical applications across a range of sectors, including e-commerce, healthcare and finance where protecting sensitive data is crucial. The outcomes and performance indicators confirm the effectiveness of the suggested system showing that it is able to be a dependable instrument for safe data transfer and communication in a world that is becoming more and more data-driven.

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