DETECTION OF GAN-GENERATED IMAGES USING SPATIAL-FREQUENCY DOMAIN FUSION DATA

A Thesis Proposal
Presented to the Faculty of the Computer Science Department
Polytechnic University of the Philippines
Sta. Mesa, Manila

In Partial Fulfillment of the Requirements for the Degree
Bachelor of Science in Computer Science

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2023

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Chapter 1

THE PROBLEM AND ITS SETTING

Introduction

The field of computer vision and image processing has been profoundly impacted by the development of Generative Adversarial Networks (GANs). GANs can produce improved synthetic images that are visually identical to real photos. However, the widespread use of GAN-generated images has also caused concern about the potential misuse of such images. GAN-generated images, for instance, can be used to fake identities, change visual information, and trick people. Therefore, the demand to provide precise detection techniques for GAN-generated images is expanding.

Figure 1. Examples of GAN-Generated Images from DALL-E

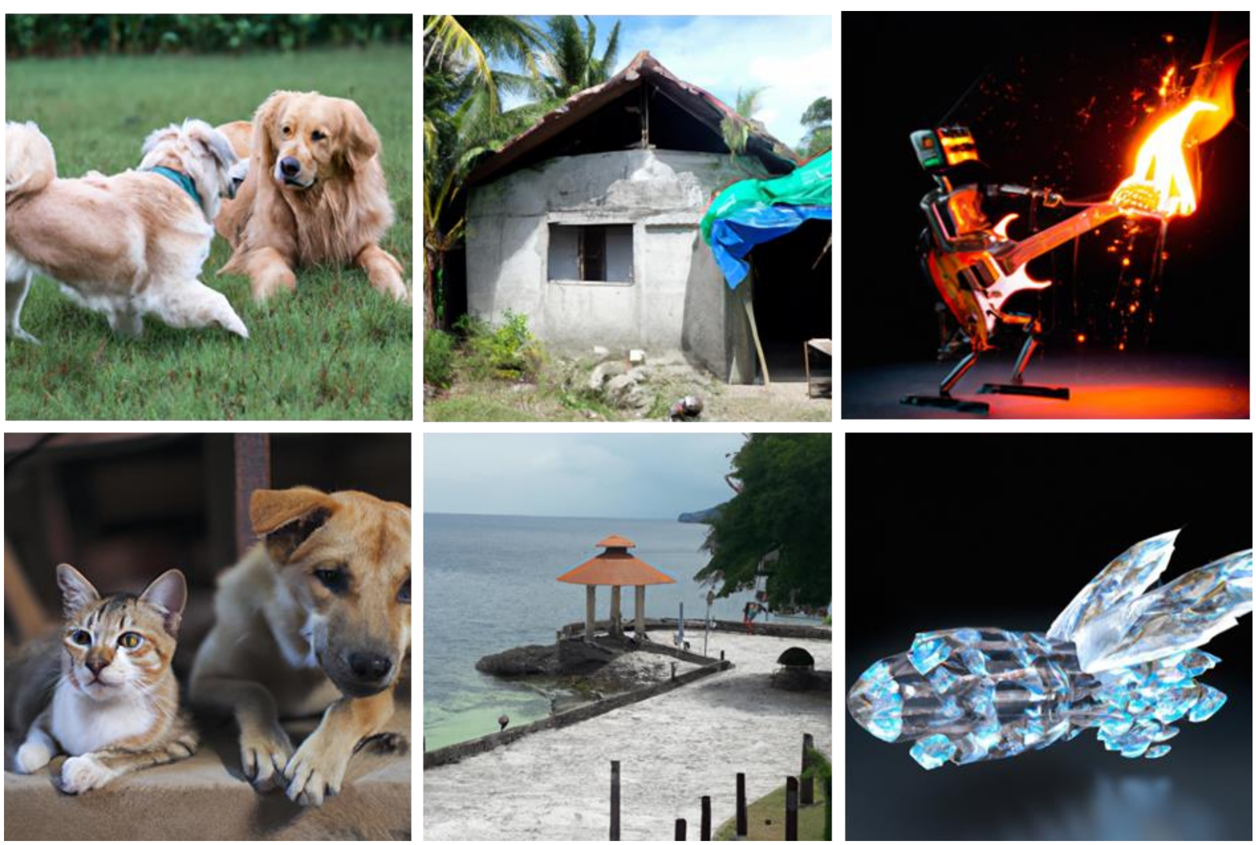


Figure 1 are some examples of GAN Generated Images. Given the success of employing GANs for picture editing, it is now possible to utilize a combination of GANs and off-the-shelf image-editing software to change digital photographs to the point where it is impossible to tell doctored images from regular ones (Nataraj, Lakshmanan, et al., 2019). Furthermore, with the capillary expansion of social networks, distributing information has become quite simple. Fake news is frequently accompanied by multimedia content to increase credibility (Marra, Francesco, et al., 2018).

Online misinformation operations have received much attention in recent years thanks to the growing prominence of social media as a way of conveying news. However, the antiquated phrase 'seeing is believing' still describes how people validate such claims. Therefore, picture forensics is becoming increasingly relevant (McCloskey, S., & Albright, M., 2018). Because for human observers, some high-resolution images created by the most recent GAN models are barely discernible from actual ones. (Zhang, X., Karaman, S., & Chang, S. F., 2019).

In recent years, researchers have developed several methods for identifying GAN-generated images based on various characteristics and classifiers in order to address this problem. While some techniques use convolutional neural networks (CNNs) to extract deep information from images, others rely on image statistics and pixel-level analysis. However, these approaches might be subject to accuracy and computational efficiency constraints.

In 2021, Bo, Liu et al., present some limitations of their methods for detecting GAN-generated images which is the difficulty in detecting GAN-generated images saved in JPEG format. Guihua Tang et al., (2021) proposed a novel approach called the Fake Images Discriminator (FID), which also faces limitations in detecting fake images of multiple types compared to detecting fake images of a single type. In 2019, Lakshmanan Nataraj et al., introduced a novel method utilizing co-occurrence matrices and deep learning. However, the effectiveness of this method in identifying GAN-generated images proved unsuccessful, highlighting the necessity for additional evaluation and generalization across different GAN architectures and datasets. Furthermore, the scalability of the method for larger datasets and real-world scenarios warrants exploration. The novel approach proposed by Michael Goebel et al., (2020) to detect, attribute, and localize GAN-generated images, which involves combining image features with deep learning methods, has limitations. Specifically, the study is limited to the specified detectors and manipulations, such as translating natural images, generating images from labeled maps of cityscapes, building facades, and satellite images, as well as generating paintings from real photos and vice versa. Xu Zhang et al., (2019) novel approach utilizing the GAN simulator concept to imitate the typical process employed by popular GAN models also faces deficiency regarding the detection of realistic-looking digital images created by the latest advances in image manipulation using GANs and off-the-shelf image-editing tools.

In this paper, the researchers will conduct a systematic experimental study to assess the performance of spatial-frequency domain fusion using Discrete Wavelet Transform (DWT) in the frequency domain and Local Binary Pattern (LBP) in the spatial domain. The study aims to evaluate the effectiveness of this novel approach for GAN detection. In line with this, the researchers will also use Support Vector Machine (SVM) as the classification algorithm, a widely recognized classifier with a successful track record in binary classification tasks. By combining DWT features from the frequency domain with LBP features from the spatial domain, the proposed concept offers a promising solution for GAN detection using the spatial-frequency domain fusion approach.

Theoretical Framework

Spatial-Frequency Feature Fusion

In the context of image classification, Spatial-Frequency Feature fusion, also known as dual-domain feature fusion, is the process of combining spatial and frequency domain features to improve the performance of a classifier. The spatial distribution of intensity values in an image is described by features called spatial domain features. While features that describe the frequency content of a picture are known as frequency domain features.

In the study conducted by Cui, Y. (2020), a novel approach to feature fusion is proposed, focusing on the fusion of dual-domain features or the fusion of spatial and frequency domain information.

Figure 2. Spatial - Frequency Feature Fusion Diagram (Cui, Y., 2020)

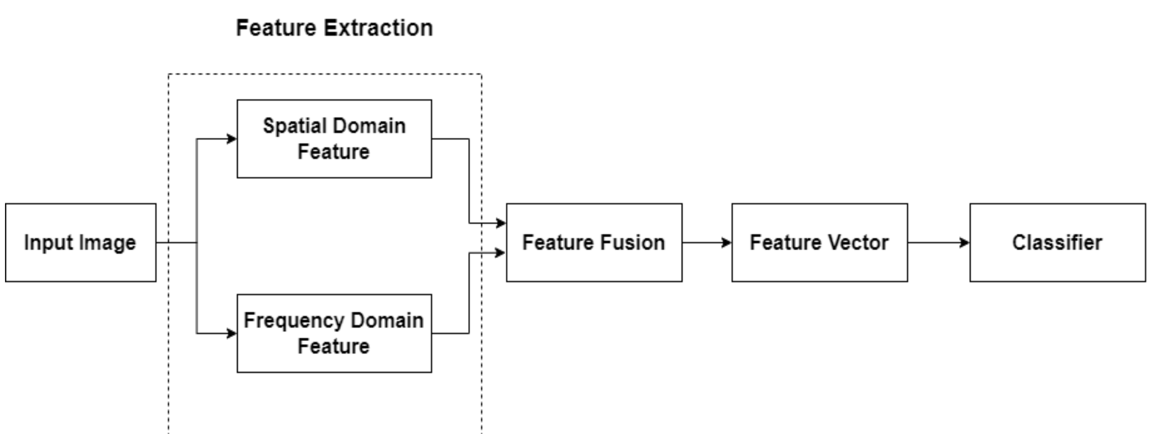


Figure 2 shows the framework of spatial- frequency feature fusion for enhanced image analyzation.

1. Firstly, features are extracted from the input image in both the spatial and frequency domains.
2. Secondly, the features extracted in the two domains are fused to form a feature vector.

3. Lastly, the feature vector is fed into the classifier for analysis.

Conceptual Framework

Figure 3. Diagram of Independent and Dependent Variable

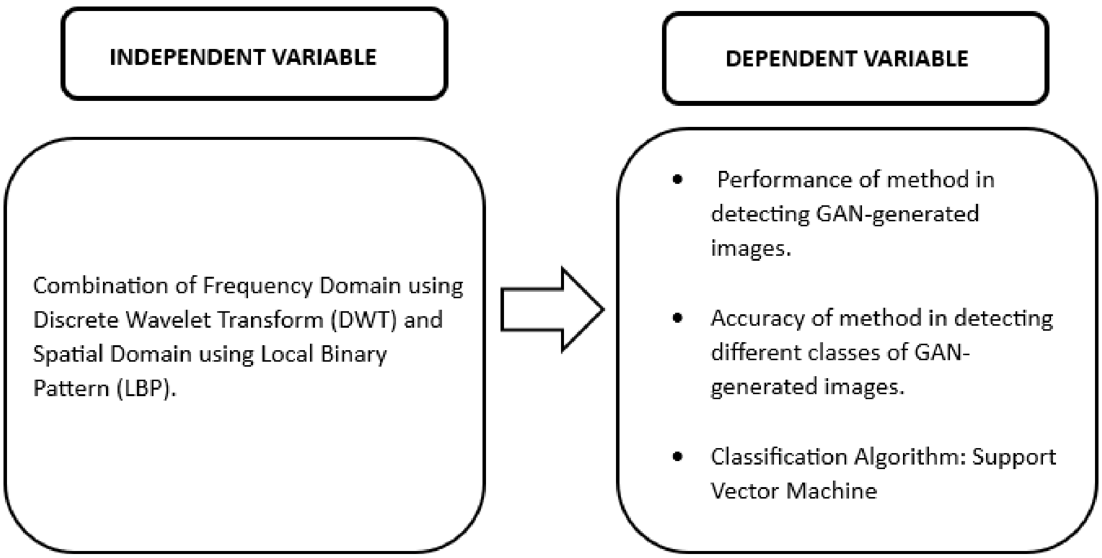


Figure 3 shows the connection between the independent and dependent variables in the study. The independent variables encompass the combination of frequency domain features using Discrete Wavelet Transform (DWT) and spatial domain features using Local Binary Pattern (LBP).

The dependent variables in this study are the performance of the method in GAN-generated image detection, including accuracy, precision, recall, and F1-score,

which is used to assess the effectiveness of the proposed method and the accuracy of the method in detecting different classes of GAN-generated images, such as Generated Faces, Animals, Objects, and Scenes. This evaluation is crucial in determining the method's accuracy for each specific class and its ability to classify GAN-generated images accurately within different categories.

To achieve these the classification algorithm employed in this study is the Support Vector Machine (SVM). SVM serves as the classification model that utilizes the extracted features from the frequency and spatial domains to predict and classify GAN-generated images.

Statement of the Problem

This study aims to evaluate the effectiveness of spatial-frequency domain fusion data (frequency - DWT and spatial - LBP) in improving the performance of detecting GAN-generated images. This research will contribute to the development of more accurate detection methods for GAN-generated images, which can have important applications in various fields, such as computer vision and security.

Research Questions

1. What is the performance of detecting GAN-generated images based on the combination of frequency domain using Discrete Wavelet Transform and spatial domain using Local Binary Pattern in terms of:
   a) Accuracy
   b) Precision
   c) Recall
   d) F1 - score
2. What is the accuracy of the method that combines frequency domain analysis using discrete wavelet transform and spatial domain analysis using local binary pattern when separately detecting each class of GAN-generated images, such as:
   a) Generated Faces
   b) Generated Animals
   c) Generated Objects
   d) Generated Scenes

Scope and Limitations of the Study

Scope of the Study

The scope of the study is centered around evaluating the effectiveness of spatial-frequency domain fusion data for detecting GAN-generated images. The primary objective is to assess the performance of the method in GAN image detection. In addition, this research will explore the proposed approach's accuracy in detecting different classes of GAN-generated images, including faces, animals, objects, and scenes. The classification algorithm Support Vector Machine (SVM) will be utilized to distinguish GAN-generated images from real images. The study focuses on addressing the challenges associated with GAN-generated image detection and aims to provide a novel and effective solution for GAN detection using the spatial-frequency domain fusion approach.

Limitations of the Study

The study's emphasis on analyzing feature fusion using specific domains (frequency DWT and spatial LBP) and a single classification algorithm (SVM) may limit the findings' generalizability to other feature extraction techniques or classification algorithms. Also, potential differences in dataset quality used for training and testing are beyond the scope of this study. Furthermore, the study does not explore the potential impact of hardware or software differences on the performance of the proposed approach, which could influence its effectiveness in real-world applications.

Significance of the Study

The significance of conducting a study on the classification of GAN-generated images using spatial-frequency domain fusion in the field of computer science can be outlined as follows:

Digital Forensic Experts. The study provides digital forensic experts with a reliable detection tool, enhancing their investigative capabilities and allowing for accurate identification and analysis of GAN-generated images, thereby strengthening the integrity of digital evidence in forensic investigations.

End Users and General Public. The study empowers end users and the general public by enabling the identification of GAN-generated images, ensuring protection against misinformation, deceptive content, and promoting trust in visual media, fostering a more informed and critical society.

Content Moderators. Content moderators may now identify and delete misleading or harmful information from online platforms because of the study's useful tool for identifying GAN-generated images. This makes it possible for content moderators to uphold the reliability and security of online environments while safeguarding users from any possible dangers posed by GAN-generated images.

Future Researchers. The study serves as a valuable resource for future researchers, providing a foundation for further exploration and advancement in the field of GAN-generated image detection. It offers insights into the effectiveness of feature extraction techniques, classifier design, and their combination, guiding future researchers in developing new approaches, algorithms, and methodologies. This fosters continued innovation and progress in the area of GAN detection and contributes to the growth of the broader field of computer vision and image forensics.

Definition of Terms

DWT (Discrete Wavelet Transform). A mathematical transformation technique used in signal and image processing. It decomposes an image into different frequency sub-bands, capturing both low-frequency and high-frequency components. DWT is employed to analyze and extract features from image data.

Feature Extraction. The process of selecting and transforming raw data (in this case, images) into a set of relevant and informative features. In this study, feature extraction techniques such as LBP and DWT are used to capture and represent distinct characteristics of GAN-generated images.

Frequency Domain. The frequency domain is a representation of an image in terms of its frequency components. It analyzes the image in the frequency space, where the image is decomposed into different frequency components. In this domain, the image is represented as a combination of different spatial frequencies, which can provide insights into the variation and distribution of patterns or features in the image.

GAN Images. It stands for Generative Adversarial Network. GAN images refer to synthetic images that are generated by a machine learning model known as a GAN. GANs consist of a generator network that creates realistic-looking images by learning from a training dataset.

LBP (Local Binary Patterns). It is a texture descriptor used for analyzing and describing the texture patterns in images. It operates by comparing the pixel values of a central pixel with its neighboring pixels, creating binary patterns. LBP is commonly used for texture analysis in computer vision and image processing tasks.

Spatial Domain. The spatial domain refers to the original representation of an image, where the image is perceived and processed based on the arrangement and values of its individual pixels. It represents the image as a two-dimensional grid of pixels, where each pixel has a specific intensity or color value.

Spatial-Frequency Domain Fusion. It is the process of combining spatial and frequency domain.

SVM (Support Vector Machine). It is a supervised machine learning algorithm used for classification and regression tasks. In the context of this study, SVM is employed as a classification algorithm to distinguish between GAN-generated images and real images based on the extracted feature

Chapter 2

REVIEW OF LITERATURE AND STUDIES

This chapter discusses the area that the researchers focused on. In this chapter, the researchers critically analyzed the existing studies related to the statement of the problem of this paper. This discusses the references similar to the main topic of this research paper.

Generative Adversarial Networks (GANs)

GANs (Generative Adversarial Networks) is a machine learning technique that has recently received much attention and popularity. GANs is a robust machine learning technique that offers new possibilities for producing synthetic data, enhancing creative applications, and tackling unsupervised learning tasks. GANs are very beneficial for semi-supervised and unsupervised learning tasks. It is a type of artificial intelligence algorithm meant to handle the challenge of generative modeling. They can use the calculated probability distribution to produce new examples. Many academics today are investigating unsupervised learning to reduce the amount of human supervision required for learning and the number of instances needed, frequently employing generative models (Goodfellow et al., 2020). The growing fascination with GANs arises from their ability to accomplish two critical things. Firstly, they can learn complex, nonlinear relationships from a latent space to a data space and vice versa, enabling deep and intricate mappings. Secondly, GANs can potentially leverage large amounts of unlabeled image data that traditional deep-learning methods struggle to access (Creswell et al., 2019).

Application of GANs in Image Generation and Manipulation

GANs have transformed picture production and manipulation by providing extraordinary possibilities for creating and modifying visual information. Using a generator and discriminator network, GANs may generate realistic and diversified images that match genuine ones in look, structure, and semantic content. This has far-reaching ramifications in art, entertainment, advertising, and design. GANs also provide extensive image manipulation capabilities, allowing users to innovatively change and transform existing images. Style transfer, in which GANs separate the style and content of an idea, and image-to-image translation, such as transforming sketches to realistic photos or changing scenes from day to night, are popular uses. GANs have expanded the scope of artistic expression and advanced computer vision applications.

In a study at NVIDIA and Aalto University, progressive growing is introduced to enhance the generated images' quality, stability, and variation in Generative Adversarial Networks (GANs). The research shows that progressive growth increases image quality by capturing finer details and delivering higher-resolution outputs. It also increases training stability, lowering the likelihood of mode collapse and providing more diversified and realistic visuals (Karras et al., 2018). By providing a style-based approach to image production, the authors solve the limitations of typical GANs. The generator in StyleGAN learns to divide the image-generating process into style and structure. The style component governs the image's high-level qualities, such as pose, lighting, and overall appearance, whereas the structure component governs the image's low-level features (Karras et al., 2019). Traditionally, generative models such as GANs require considerable training data to understand the underlying distribution and create new samples. However, in many real cases, getting such datasets might be difficult, if not impossible. SinGAN solves this restriction by offering a novel approach to learning a generative model from a single natural image. The main idea is to train a hierarchical generative model that captures the multi-scale features and textures of the input image. SinGAN also supports picture manipulation and editing. Users can adjust specific aspects or qualities of the generated images while maintaining overall coherence and realism by perturbing the generative model's latent space (Shaham et al., 2019).

Challenges in Detecting GAN-generated Images

Detecting GAN-generated fake images is critical, especially in scenarios where visual content authenticity is vital, such as forensics or data integrity. GANs, on the other hand, have gotten increasingly sophisticated at generating realistic and high-quality images, making detection difficult. The study reveals many significant issues in recognizing GAN-generated images. For starters, GANs can produce pictures that closely resemble real ones, making it difficult to distinguish between the two. Second, as GANs have improved in creating images with various styles, it has become more difficult to specify a specific collection of traits or patterns that can consistently detect GAN-generated fakes (Riccio et al., 2019).

Overview of Image Forensics and its Significance

Image forensics is a branch of digital forensics that deals with the analysis of digital images to determine their authenticity and integrity. It can be used to identify forgeries, tampering, and other alterations to images. Image forensics can also be used to extract information from images that are not visible to the naked eye, such as EXIF data or hidden messages. Images are used in a wide variety of applications, including law enforcement, intelligence gathering, and journalism. In these applications, it is essential to be able to verify the authenticity and integrity of images.

Forensic imaging prevents the loss of original data. These imaging tools and techniques are the only way to ensure that electronic data can be successfully admitted as evidence in a court or legal proceeding (Kervin, P. 2023).

A detailed image of a memory system or primary storage device provides accurate information on the contents of the device, enabling forensic experts to diagnose existing and potential problems. However, for a legal or compliance audit as part of a forensic investigation, law enforcement needs accurate and verifiable data (Kervin, P. 2023).

Spatial Domain Analysis

The spatial domain refers to the representation of an image as a 2D matrix or grid of pixel intensities. Each element in the matrix represents the intensity value of a pixel at a specific location in the image. The spatial domain operations involve manipulating the pixel values directly, such as filtering, enhancement, or transformation of the image. It is called the spatial domain because it operates directly on the spatial arrangement of pixels in the image.

Spatial domain analysis is a fundamental approach in image analysis , it involves directly processing the image data in its original spatial arrangement without any transformations. This analysis aims to extract meaningful information and interpret it based on the characteristics of individual pixels or local neighborhoods. By analyzing the spatial distribution, intensity, texture, and other pixel-level attributes, spatial domain techniques provide valuable insights into image content and facilitate various image processing tasks.

The spatial domain techniques have found widespread use in digital image processing problems because of their simplicity and ease in software and hardware implementation.Some methods focus on pre-processing steps, such as texture analysis using techniques like the gray-level co-occurrence matrix (GLCM) (Asmara et al., 2018). GLCM calculates statistical measures that describe the spatial relationships between pixels, providing information about image texture. Post-classification techniques also exist to refine and improve classification results based on spatial information.Other techniques involve incorporating spatial information during the classification process itself, such as using classifiers that consider spatial relationships between neighboring pixels. One of the spatial domain techniques is the Local Binary Pattern

Local Binary Pattern, which was introduced by Ojala et al., (2002) is an approach to extract local features from images by computing the local differences in intensity between the value of the center pixel and its surrounding pixel (neighboring pixels). The aim of the local binary pattern is detecting different patterns using the differences between the neighboring pixels and its center pixel. Patterns are then aggregated to describe the whole image.

Equation 1. Local Binary Pattern

$$LBP_{P,R}(x,y) = \sum_{p=0}^{P-1} s(i_p - i_c) \times 2^p \text{ where } s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Where ic and ip are, respectively, gray-level values of the central pixel, and P surrounding pixels in the circle neighborhood of radius R. s(.) is the sign function. Second, the decimal value corresponding to the resulting binary neighborhood is computed. Thereafter, a summation of the obtained values is performed to produce the LBP code that represents the local structure around the considered pixel.

Consequently, LBP have been used with enormous applications such as image classification (Haseela, 2022) texture classification (Ningtyas etal., 2022), face recognition(Shamsul et al., 2018), fingerprint identification (Gornale, 2018) and medical image classification (Narin et al., 2021). The most significant properties of LBP include its robustness to monotonic gray scale variations and simplicity in computations, thus making analysis of images in challenging real-time settings easier.

Local Binary Patterns (LBP) and its Applications in Image Texture Analysis

Texture analysis has proven to be a breakthrough in many applications of computer image analysis. It has been used for classification or segmentation of images which requires an effective description of image texture, texture mainly describes the surface properties of the corresponding object, and reflects the gray-scale distribution of the image in the spatial domain. (Ribas et al., 2020) Due to high discriminative power and simplicity of computation, the local binary pattern descriptors have been used for distinguishing different textures and in extracting texture.

In the study conducted by Goyali et al., (2020) it focuses on the application of texture analysis for detecting bleeding regions in human intestines using local binary pattern (LBP) descriptors. The authors discuss the performance of various texture classification techniques, including Contourlet Transform, Discrete Fourier Transform, Local Binary Patterns, and Lacunarity analysis. The study demonstrates that incorporating efficient image segmentation, enhancement, and texture classification using the LBP descriptor enables precise detection of bleeding regions in gastrointestinal images.

Akmalia et al., (2019) proposed a method for introducing the shape, color, and texture of skin diseases in digital images and classifying the results of image analysis based on the type of disease in human skin. They use a combination of Local Binary Pattern (LBP) and Convolutional Neural Network (CNN) as a classifier which can later be used as sensors or vision for skin diseases automatically. The results of this study can help in the early identification of skin diseases, helping parties who want to know the image value of skin diseases by using LBP and classifying it based on the type of disease using CNN. This study shows the level of accuracy of combining LBP with CNN is quite high with an average value of 92%.

In another study conducted by Aruraj et al., (2019) they proposed a method for detecting and classifying diseases in banana plants using local binary pattern (LBP) texture analysis and support vector machine (SVM) classification. Consist of two primary phases; (a) extraction of texture features from using local binary pattern (LBP); (b) classification of banana plant diseases and healthy banana plant. The texture features using LBP are extracted from an enhanced input image. The extracted features are fed to Support Vector Machine (SVM) and K-nearest neighbor (KNN) for final banana plant disease classification. The proposed methodology attained an accuracy of 89.1% and 90.9% for two experimental cases using SVM classifier.

In facial recognition was performed using LBP and CNN. The results of LBP + CNN performance evaluation showed an accuracy of 95.33% compared to CNN performance evaluation with an accuracy of 91.83%. (Zhang et al., 2017) Similar results are also shown in the study proposed by (Elmahdy et al., 2017) where the use of LBP and classifier Support Vector Machine (SVM) shows an accuracy of 98.67% in AlexNet's modification of the classification of low-quality skin images.

Local Binary Patterns (LBP) have emerged as a powerful technique in image texture analysis. Its simplicity and discriminative power make it suitable for distinguishing different textures and extracting texture information. LBP has been successfully applied in various domains. These studies demonstrate the effectiveness of LBP in capturing texture information and its potential for accurate classification and detection tasks. The combination of LBP with other techniques such as Support Vector Machine (SVM) and Convolutional Neural Network (CNN) further enhances its performance, achieving high accuracy rates in various applications.

Relevant Studies Utilizing LBP for Image Manipulation Detection

Image manipulation detection is an important area of research in the field of computer vision and forensic analysis. Local Binary Patterns (LBP) has been successfully utilized in several studies for detecting image manipulations and tampering.

In the study conducted by Mahale et al., (2017) they focused on identifying inconsistencies in digital images. The paper outlined several steps, including preprocessing, feature extraction, and matching processes, emphasizing the effective use of the local binary pattern (LBP) method for feature extraction. The matching measure employed in the study was Euclidean distance. The results demonstrated that utilizing LBP with a block size of 2x2 yielded the best accuracy, reaching approximately 98.58% for automatic detection of inconsistencies in an image.

Srivastava et al., (2020) proposes an image hashing technique based on Local Binary Pattern (LBP) for image identification and content-based image copy detection. The objective of this technique is to differentiate duplicate copies of images from their original ones. With the availability of numerous image editing software, the duplication of large original images has become a common issue. The proposed approach aims to address this problem by utilizing the

Local Binary Pattern algorithm. In the proposed technique, the input image undergoes a preprocessing step to remove minor effects. Then, the Local Binary Pattern (LBP) algorithm is applied to the processed image, which produces features used for image identification. The experimental results indicate that the proposed hashing technique performs exceptionally well against the "Histogram equalization" attack. The Receiver Operating Characteristics (ROC) curve demonstrates that the proposed hashing method outperforms other referenced techniques in terms of robustness and discrimination. The paper emphasizes the robustness of the proposed technique to different attacks, apart from performing well against the Histogram equalization attack. It also suggests that the proposed method can be utilized for online detection of image copies and content-based image authentication in large-scale image databases.

In another study of Kaushik et al., (2019) they proposed an approach in order to detect authentic and tampered images by incipiently implementing the LBP (Local Binary Pattern) descriptor on the image and then the HOG (Histogram of Oriented Gradients) descriptor is applied on the extracted LBP features and finally they are classified into the two different classes: Authentic Images and Tampered Images, adopting the Support Vector Machine (SVM). The structured model implemented on the CASIA 1 and CASIA 2 databases signifies 92.3% and 96.1% rate of detection respectively. The time complexity is also considerably reduced and the method is found to be functioning well under diverse illuminating variation conditions. The future work objective is improving the performance accuracy of the method in the medical images and in multimedia (video) applications.

Local Binary Patterns (LBP) have been successfully utilized in various studies for image manipulation detection and tampering analysis. The studies mentioned provide valuable insights into the effective use of LBP in different aspects of image manipulation detection.

Limitations and Challenges of Spatial Domain Analysis

Spatial domain analysis heavily relies on the availability and quality of spatial data. Inadequate or incomplete data can limit the accuracy and reliability of analysis results. Data collection efforts, data integration, and data preprocessing techniques play a vital role in mitigating these challenges.

In spite of the substantial success of local binary patterns in various applications in computer vision, the LBP operator comes with some limitations. It generates long histograms which are also rotation sensitive. Moreover, they are sensitive to noise. Also, it is difficult to determine the

large scale structures in an image. Thus, they miss out on some local structures in certain circumstances.

One limitation lies in the fact that limiting the spatial window size on only 3 × 3 neighborhoods can lead to inability to capture dominant features with large scale structures. Furthermore, the LBP discrimination performance shows some limitations especially when irregular textures patterns are present in the image. (Kaddar et al., 2017)

They also added that such approaches work well in noisy environments, allowing more enhancement of robustness, and can capture local patterns more accurately, but they increase the computational complexity. In some cases, only a single resolution is sufficient to obtain a very good discrimination.

In study of Fu et al., The existing local binary pattern (LBP) operators have three disadvantages: (1) They produce rather long histograms, which slow down the recognition speed especially on large-scale face database; (2) Under some certain circumstance, they miss the local structure as they don't consider the effect of the center pixel; (3) The binary data produced by them are sensitive to noise

While spatial domain analysis and specifically Local Binary Pattern offer valuable insights into spatial data, it is important to acknowledge its limitations and challenges. It is needed to consider these limitations and employ appropriate data collection, integration, preprocessing techniques, and alternative methods to address these challenges. By doing so, they can enhance the accuracy, reliability, and interpretability of spatial analysis results, enabling better decision-making in various domains.

Frequency Domain Analysis

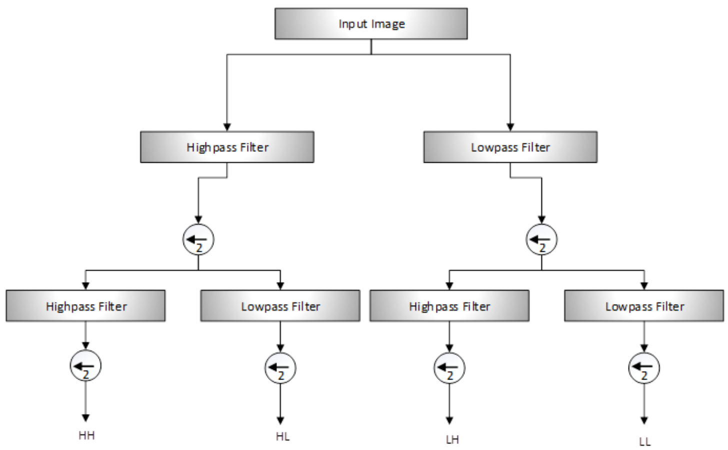
According to Gonzalez, R. C. & Woods, R. E. (2018): In image processing, the frequency domain is a representation of an image in terms of its frequency components. The frequency components of an image represent the spatial frequencies of the image, which are the rates at which the brightness of the image changes from one pixel to the next. The frequency domain can be used to perform a variety of image processing tasks, such as filtering, sharpening, and edge detection.

Frequency-domain analysis is a fundamental tool in signal processing applications. It plays a crucial role in various fields, such as communications, geology, remote sensing, and image processing. By focusing on the frequency domain, we gain insights into how the energy of a signal is distributed across different frequencies. This analysis provides valuable information about the individual frequency components and the required phase shifts for reconstructing the original signal.

Discrete Wavelet Transform

There are several techniques used to analyze images in the frequency domain and one of those is the Discrete Wavelet Transform (DWT). It is a mathematical technique that can be used to decompose an image into its low and high frequency components. A signal is passed through two filters, high pass and low pass filters. The image is then decomposed into high frequency (details) and low frequency components (approximation). The approximation shows the overall pattern of pixel values as well as the specifics such as the horizontal, vertical, and diagonal components (Chandrasekaran K, 2021). The decomposition yields four distinct sub-bands: low-low (LL), low-high (LH), high-low (HL), and high-high (HH) as illustrated in Figure 4.

Figure 4. General Flow Diagram of Discrete Wavelet Transform by Aamir et al.,



According to Mohsin et al., (2020) the utilization of wavelet analysis techniques has greatly advanced the field of image processing, enabling significant progress in areas such as image compression, image denoising, and image enhancement.

Image compression is a crucial application of wavelet transforms in image processing. Wavelets are mathematical functions that allow for the representation of data or other functions. Wavelet transforms break down an image into different frequency components, which can be further divided into sub-images with different frequency elements. This decomposition allows for efficient compression of the image while preserving important features. Wavelet compression algorithms have been shown to provide better compression and quality compared to traditional methods like JPEG. Image denoising is another important application of wavelet transforms. Image processing often introduces noise, which degrades the quality of the image. Wavelet transforms can help in reducing noise while preserving the important signal features. Denoising techniques using wavelet transforms involve computing the wavelet transform of the noisy signal, modifying the wavelet coefficients based on certain rules, and then computing the inverse wavelet transform using the modified coefficients. Different thresholding strategies can be employed for denoising in various scenarios. Image enhancement is a technique used to improve the quality and clarity of images. Wavelet-based image enhancement techniques include contrast enhancement, enhanced graph versions and formulas, smooth filtering, retinex, single or multi-band retinex, and multi-band wavelet transformation. These techniques aim to recover lost information in an image caused by factors such as poor lighting conditions, incorrect exposure, or weather conditions.

In addition to that, DWT is also popular in feature extraction and many studies in the image processing field used this as a technique to extract features of an image. The purpose of feature extraction is to represent the image in its compact and unique single values or matrix vector. In the study conducted by Kutlu et al., (2019) they made use of DWT as one of the techniques together with CNN for classifying liver and brain tumors. The single-level one-dimensional discrete wavelet transform was used to minimize but strengthen the feature vector acquired by CNN.

Discrete Wavelet Transform in Image Manipulation Detection

The Discrete Wavelet Transform (DWT) became known as a strong technique in the field of image processing for detecting manipulated images. DWT identifies small discrepancies caused by operations such as image splicing by decomposing an image into several frequency sub bands which makes it easier to perform multi-resolution analysis. Several studies in image manipulation detection were conducted utilizing DWT as a technique.

In the study conducted by Hakimi et al., (2015) they made use of Discrete Wavelet Transform (DWT) as a crucial component in their image manipulation detection approach. By converting the image into the YCbCr color channel and applying the Local Binary Pattern (LBP) operator and DWT to non-overlapping blocks, they were able to extract meaningful features. These features were further analyzed using Principal Component Analysis (PCA) and classified using a Support Vector Machine (SVM), resulting in an efficient method for exposing image splicing forgeries. The successful integration of DWT with other techniques demonstrates its significance in achieving accurate manipulation detection.

Subramaniam et al., (2019) investigates the use of the Discrete Wavelet Transform (DWT) in the context of picture splicing forgery detection. Their proposed method combines DWT with two other techniques to improve picture tamper detection accuracy. The DWT coefficients or the redundant discrete wavelet transform (RDWT) to be specific are used as features for the detection. By assessing these coefficients and taking into account the blurring of boundaries inside the tampered regions, the method outperforms other algorithms in picture splicing detection. The efficiency of including DWT into the entire strategy is demonstrated by experimental assessment on public picture datasets, giving a robust solution for reliable detection of image splicing frauds.

Fusion of Spatial and Frequency Domains

The individual utilization of spatial domain and frequency domain analysis in the field of image processing possessed several weaknesses or limitations. While several algorithms have been developed for each domain, they exhibit inherent disadvantages when used independently. In the context of noise removal, Hirani & Totsuka (2004), showcase the weaknesses of the two domains. Frequency domain algorithms can capture the global structure of an image but lack control, resulting in blurred lines and loss of sharpness. On the other hand, spatial domain algorithms have local control but lack information about the global structure of the image, limiting their effectiveness. Combining both spatial and frequency domain information is necessary to overcome these weaknesses and to improve the process of image denoising.

Existing Approaches for Spatial-frequency Fusion in Computer Vision and Image Processing

Several studies in the field of image processing have explored the effectiveness of spatial and frequency domain feature fusion for a more improved analysis in various topics. In 2014, Zhou R. proposed a method for texture retrieval using spatial and frequency domain-based feature fusion aiming to leverage the strengths of the two said domains. The study utilizes sober and histogram features for spatial analysis and Fourier analysis for frequency domain exploration, conducting different experiments in each domain. The retrieved features from both domains are then combined using a feature fusion scheme. The MIT texture database is used to assess the effectiveness of the suggested strategy, producing encouraging experimental outcomes. Through its demonstration of the effectiveness of merging spatial and frequency domain information for improved performance, this study makes a contribution to the field of texture retrieval. Sun et al., (2019) presented a novel object detection algorithm that combines spatial and frequency domains to address the challenges in surface floating object detection. In order to gather both global and local information, the algorithm starts with rough texture recognition in the spatial domain using a combination of FHOG and GLCM. Then, based on the new texture properties, sliding windows are classified using Support Vector Machines (SVM). To help to remove redundant regions brought on by interferences and preserve floating objects in complex sceneries, a frequency-based saliency detection technique has been developed. It utilizes the use of both global and local low-rank decompositions. The combination of bounding boxes from multiple processing domains provide the final detection result. The suggested method outperforms traditional image segmentation, saliency detection, manually constructed texture detection, and CNN-based object detection methods, according to experimental data. Particularly, the suggested technique demonstrates significant anti-interference abilities in complex water scenarios and only needs a small number of training samples. The typical accuracy achieved by the proposed method is 97.2%, with a low time consumption of only 0.504 seconds.

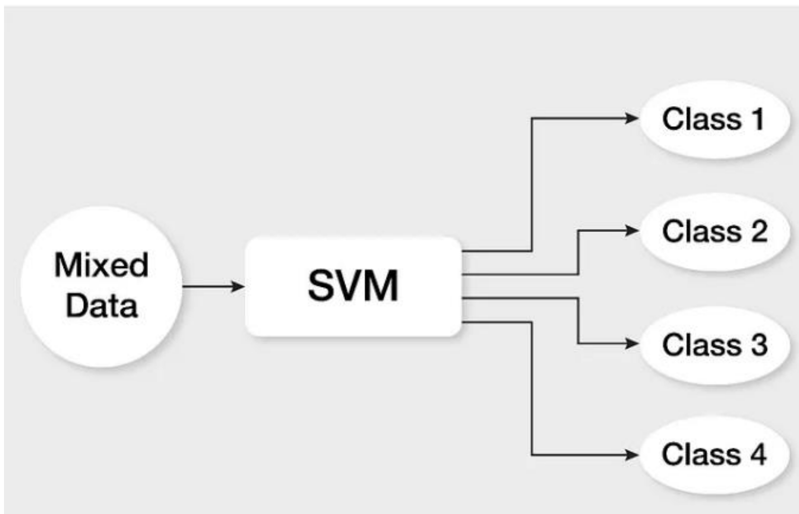
In another study conducted in 2020, Cui presents a novel approach to no-reference image quality assessment (IQA). The method named DFF-IQA uses dual domain feature fusion to combine features taken from the frequency and spatial domains. In the frequency domain, features like spectral entropy, oriented energy distribution, and fitting parameters of an asymmetrical generalized Gaussian distribution are taken into account, while features related to weighted local binary pattern, naturalness, and spatial entropy are extracted in the spatial domain. A feature vector with quality awareness is produced by fusing these features. The association between image attributes and quality score is then established using a random forest-based regression approach, giving an overall assessment of image quality. Using the LIVE database, the effectiveness of DFF-IQA is assessed and contrasted with that of other current IQA models. In comparison to competing IQA approaches, experimental findings show that the suggested DFF-IQA method achieves a higher consistency with the human visual system.

The study by Pan et al., (2019) proposes a visual saliency detection method based on the fusion of spatial and frequency domain analysis. Firstly, the image is smoothed by a Gaussian filter and then segmented by the superpixel segmentation of SLIC. The spatial saliency map is calculated by the color distance. Secondly, the saliency map of frequency domain is obtained by hypercomplex Fourier transform. Finally, the point multiplication operation is adopted to merge the spatial and the frequency domain saliency map. Compared with other traditional models, their proposed model can highlight the target, suppress the background, and the results obtained are more accurate and stable, but also have clear boundaries. In the future researchers , they suggested to improve the model and have a better detection effect in a less contrast environment.

Introduction to Support Vector Machines and Their Applications

Support Vector Machine (SVM) was first heard in 1992, introduced by Boser, Guyon, and Vapnik in COLT-92. Support Vector Machine (SVM) is a classification and regression prediction tool that uses machine learning theory to maximize predictive accuracy while automatically avoiding overfitting to the data. Support Vector Machines can be defined as systems that use the hypothesis space of linear functions in a high-dimensional feature space. They are trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory.

Figure 5. Support Vector Machine Classifier by Pupale R.



According to Cervantes et al., (2019) SVMs are one of the most powerful and robust classification and regression algorithms used in various fields. It can solve linear and non-linear problems and work well for many practical problems (R. Pupale, 2018).

In the study titled "Applications of Support Vector Machine (SVM) Learning in Cancer Genomics," SVM learning is employed for cancer genomic classification or subtyping. The classification feature of SVMs is expanding its use in cancer genomics, leading to the discovery of new biomarkers, new drug targets, and a better understanding of cancer driver genes.

SVM-based Image Classification Methods for Authenticity Verification

According to Kaur, C. deep, & Kanwal, N. (2019), images have the potential of conveying much more information as compared to the textual content. People pretty much believe everything that we see. In order to preserve/check the authenticity of images, image forgery detection techniques are expanding its domain. Detection of forgeries in digital images is in great need in order to recover the people's trust in visual media.

Singh et al., (2018) proposed a methodology for detection of image splicing forgery using the blind approach i.e., passive method to detect the spliced region in the digital image. This paper mainly concerns the image splicing forgery and it initiates with the DWT (Discrete Wavelet Transform) method, which will decompose the image into sub images and obtain coefficients for each sub image. After that for feature extraction SURF (Speed-Up Robust Features) will be used and finally SVM (Support Vector Machine) will perform classification for splicing forgery detection in digital image.

Studies Employing SVM for Classifying GAN-generated Images

The rise of Generative Adversarial Networks (GANs) has introduced challenges in distinguishing between real and GAN-generated images. Tang et al., (2020) present a method that employs DWT for feature extraction and the final feature used for classification is a set of three-dimensional vectors in a simple form. LibSVM is used in this study to implement a simple binary classifier, and the radial basis function (RBF) kernel is used to train the SVM for classification.

McCloskey, S., & Albright, M. (2019) proposed a specific cue which can be used to distinguish GAN imagery from real imagery. Since generators use different structures from one GAN to another, features which are common among GANs are looked at. Also, in order to improve the detectability, the focus is on the later layers of the generator, since cues introduced in these layers are less likely to be modulated by subsequent processing. McCloskey, S., & Albright, M. (2019) These features are classified by a linear Support Vector Machine (SVM), trained using Matlab's fitcsvm function. The training data consisted of features from 1387 GAN generated images (randomly sub-sampled from the 30 LSUN categories of images created by the GAN in, and real camera images from the ImageNet dataset.

Agarwa, H., & Singh, A. (2021) proposed a method that will use the SVM classification method to train our classifier. Firstly, the SVM classifier will divide the transformed Information into two parts one for training and the other one for testing. The method will use 80% of transform data to train the classifier engine and then the remaining 20% of the data to check the accuracy of the proposed method.

Hakimi et al., (2015) proposed a method that introduces an image splicing forgery detection based on LBP, wavelet transform and PCA which finally, all extracted features are fed to a SVM classifier, which detects whether an image is fake or original.

Existing Methods to Detect GAN-generated Images

The study conducted by Liu et al., (2022) performs image authentication by checking whether an image follows the patterns of authentic images. The experiments show that a simple classifier using noise patterns can easily detect a wide range of generative models, including GAN and flow-based models. The proposed method achieves state-of-the-art performance and outperforms existing methods in image authentication. Due to the superior generalization ability of the method, it can be utilized in realistic scenes, even with future unseen models

In another study conducted by Tang et al., (2021) converts the color image into three color components of R, G, and B. Discrete wavelet transform (DWT) is then applied to RGB components separately. Finally, the correlation coefficient between the subband images is used as a feature vector for authenticity classification. The suggested method is effective at identifying GAN-synthesized fake images and is robust to typical perturbation attacks.

The study “Detecting GAN generated Fake Images using Co-occurrence Matrices” by Nataraj et al., (2019) proposes a novel approach to detect GAN generated fake images using a combination of co-occurrence matrices and deep learning. They extract co-occurrence matrices on three color channels in the pixel domain and train a model using a deep convolutional neural network (CNN) framework. The study's findings reveal that co-occurrence matrices possess the ability to capture distinctive statistical properties that differentiate real images from GAN-generated fake images. By examining the co-occurrence matrices of both real and fake images, discernible disparities in texture patterns and statistical attributes can be observed. The proposed method demonstrates high accuracy in discriminating between real and fake images across diverse GAN architectures, encompassing Deep Convolutional GANs (DCGANs) and Wasserstein GANs (WGANs). Moreover, the method proves to be robust against common real-world image transformations and perturbations.

In another study conducted by Goebel et al., (2020) proposed a novel approach to detect, attribute and localize GAN generated images that combines image features with deep learning methods. For every image, co-occurrence matrices are computed on neighborhood pixels of RGB channels in different directions (horizontal, vertical and diagonal). A deep learning network is then trained on these features to detect, attribute and localize these GAN generated/manipulated images. The findings indicate that the proposed model performed exceptionally well on various image scales and JPEG compression factors. Through detailed experiments on a vast dataset of over 2.7 million GAN and authentic images from different major GAN datasets, the model demonstrated its effectiveness. Furthermore, the visualization using t-SNE with deep features from the neural network showed promising results in distinguishing between GAN-generated and authentic images using the proposed method.

The study conducted by Zhang et al., (2019) proposes a GAN simulator, AutoGAN, which can simulate the artifacts produced by the common pipeline shared by several popular GAN models. Additionally, we identify a unique artifact caused by the upsampling component included in the common GAN pipelines. The findings indicate that the researchers conducted a study on the artifacts caused by the up-sampling component of GAN pipelines in the frequency domain, aiming to develop robust classifiers for identifying fake GAN images. Instead of using image pixels, they proposed employing the frequency spectrum as input for training the classifier, resulting in significant improvement in its ability to generalize. Additionally, they introduced AutoGAN, a simulation framework that trains common GAN pipelines and generates GAN artifacts within real images. This allowed them to train a GAN fake image classifier without relying on fake images as training data or specific GAN models. The spectrum-based classifier derived from AutoGAN demonstrated strong generalization capabilities for fake images produced by GANs with similar structures.

Identification of Research Gaps

Some of the proposed methods conducted by Liu et al., (2022) includes state-of-the-art performance and outperforms existing methods in image authentication. In this study, the "Learned Noise Pattern" method examines the consistent presence of distinct noise patterns in authentic images, which significantly differ from those found in fake images. These identified patterns are then employed as distinguishing features for the purpose of detection. However, the method does not work well in JPEG compression in a case where it generates multiple periodicities in generated images.

The study conducted by Tang et al., (2021) proposed the fake images discriminator (FID) approach, which identifies GAN-generated fake images by analyzing the spectral correlation in natural color images. The method divides the image into R, G, and B components, applies discrete wavelet transform (DWT) individually to each component, and utilizes the correlation coefficient between subband images as a feature vector for authenticity classification using the Support Vector Machine classifier. However, its gaps indicate that the performance of detecting fake images decreases when dealing with multiple types of fake images compared to a single type.

This is because the content of fake images of different types varies significantly, leading to a more dispersed distribution of the extracted feature vectors in the hyperplane.

According to Nataraj et al., (2019) co-occurrence matrices offer the ability to distinguish real images from GAN-generated fakes based on distinctive statistical properties. The method analyzes the matrices to identify texture pattern and statistical differences, achieving high accuracy across various GAN architectures. However, further research is needed to evaluate generalizability, scalability, vulnerability to adversarial attacks, and comparison with existing techniques in detecting fake images.

According to Goebel et al., (2020) a novel approach combining image features and deep learning methods is used to detect, attribute, and localize GAN-generated images. Co-occurrence matrices are computed by analyzing neighboring pixels in the RGB channels, and a deep learning network is trained to perform identification, attribution, and localization tasks for GAN-generated images. However, the study's focus is limited to detecting fake images generated by specific methods and manipulations, such as image-to-image translation and generation of images from labeled maps. Additionally, the research gap exists in evaluating the performance of the approach in real-world settings beyond Twitter, especially in social networks. Further research is needed to explore the performance and applicability of the proposed method in diverse social media platforms and real-world scenarios.

According to Zhang et al., (2019) a novel approach is introduced that leverages the GAN simulator concept to mimic the process employed by popular GAN models. This simulator-based approach eliminates the need for developers to have access to the actual GAN models during classifier training. The researchers also investigate the impact of the up-sampling component of GANs and propose a fresh approach to designing the classifier based on signal processing analysis focused on the input spectrum. While the study successfully detects and attributes GAN-generated images using major GAN datasets, there still exists a research gap in detecting realistic-looking digital images created through the latest advancements in image manipulation using GANs and readily available image-editing tools. Further research is needed to address the detection challenges posed by these advanced techniques and tools in order to enhance the overall detection capabilities in practical scenarios.

Synthesis of the Reviewed Literature

An overview of the evaluated literature on GAN-generated images, image forensics, and authenticity verification methods is given in this literature synthesis. It starts with an introduction of GAN-generated images, emphasizing its function in creating realistic images and the difficulties they provide for forensic investigation and authenticity verification. The literature then explores various methods for authenticating images and conducting picture forensics, highlighting the significance of these methods in preventing image alteration and forgeries. It examines spatial approaches including edge detection, local statistics, and noise analysis as well as frequency domain techniques like the Fourier Transform and Discrete Wavelet Transform. The unification of the spatial and frequency domains is also covered in the synthesis, with methodologies that do so are highlighted for more thorough image analysis. The article finishes with a comparison of existing. The synthesis also discusses the fusion of spatial and frequency domains, highlighting approaches that combine these techniques for more robust image analysis. Finally, it concludes with a comparative analysis of existing methods and identifies research gaps in the field.

The proposed method for detecting GAN-generated images using Spatial Frequency Feature Fusion is a novel and promising path for further research in the field of image forensics and authenticity verification. This method stands out since there has been no previous research that has particularly explored it in the context of GAN-generated image detection. This approach capitalizes on the strengths of both domains by integrating spatial and frequency domain techniques, providing a more thorough and robust analysis of GAN-generated images. The Spatial Frequency Feature Fusion method has the advantage of using the particular properties of GAN-generated images that are typically difficult to detect using traditional forensic methods.

GAN-generated images have a high level of realism and can closely resemble genuine images, making separation and identification from real images challenging. This method attempts to capture tiny abnormalities and inconsistencies caused by GANs in diverse domains by integrating spatial and frequency information, thus enhancing detection accuracy. Given the present research gaps and advantages, investigating the Detection of GAN-generated images using Spatial Frequency Feature Fusion has tremendous potential for expanding the field of image forensics and authenticity verification. It may contribute to the creation of more sophisticated and reliable techniques for identifying GAN-generated images, combating image forgeries, and ensuring the integrity of visual content in a variety of domains such as digital forensics, media authentication, and content verification.

Chapter 3

METHODOLOGY

This chapter discusses the system architecture, instruments used, the procedure of data gathering, development details, and the statistical treatment of the data.

Research Design

The study will utilize a true experimental design, which is a systematic and scientific approach that allows for rigorous evaluation of the effectiveness of spatial-frequency fusion data in detecting GAN-generated images. In this design, the researcher will manipulate specific variables related to the spatial and frequency domains. By manipulating these variables, the study aims to investigate the effect of combining spatial and frequency features on the performance of the classifier in the context of GAN detection.

The proposed approach focuses on spatial and frequency data fusion, which entails combining information from both domains to provide a more thorough representation of the GAN-generated images. This fusion aims to capture important visual patterns and attributes that can help determine whether an image was created by a GAN or not.

The study signifies more control over the variables involved by using a true experimental design, limiting potential confounding effects and allowing for a more accurate evaluation of the link between the fusion of spatial and frequency data and classification accuracy. The design also aids in determining the existence of a cause-and-effect connection, as any modifications in classification accuracy can be related to changes in the spatial-frequency fusion variables.

In summary, this research design provides a systematic and scientific framework for investigating the effectiveness of spatial-frequency fusion data in GAN-generated image detection, contributing to the development of GAN detection techniques, and improving our understanding of how different image features impact classification performance.

Sources of Data

Multiple datasets were used in the study to examine a broad range of generative adversarial network (GAN) applications. The real images were collected from various dataset classes, including Faces, Animals, Scenes and Real Objects. These diverse dataset classes were chosen to ensure a comprehensive representation of different image categories and to capture a wide range of visual characteristics. The source of real images will be gathered from kaggle which is an online platform that provides a vast collection of diverse and high-quality datasets for data analysis and modeling. In addition to the real images, GAN-generated images were also included in the dataset, which will come from StyleGAN3.

Table 1. List of Real and GAN-generated images

Faces	1000	Generated Faces	1000
Animals	1000	Generated Animals	1000
Objects	1000	Generated Objects	1000
Scenes	1000	Generated Scenes	1000

A total of 8,000 images will be collected, with both real and GAN-generated examples included.

Research Instrument

GAN-Generated Images Detection Tool: A software tool that the researchers will develop to classify an image as fake or real and to know if the proposed method has an impact on the performance of the detection tool

Experiment Paper: This will be utilized to collect the findings of the experiment utilizing the GAN-generated image detection tool.

Contents of the Experiment Paper:

- **Objective**
- **Materials and/or Equipment**
- **Procedure**
- **Result**

Table 2: Sample Table for evaluating the tool developed in detecting GAN-generated images

Image	Expected Result	Actual Result	Evaluation

Table 3: Sample Table for evaluating the performance of the proposed model in terms of accuracy, precision, recall and f-measure

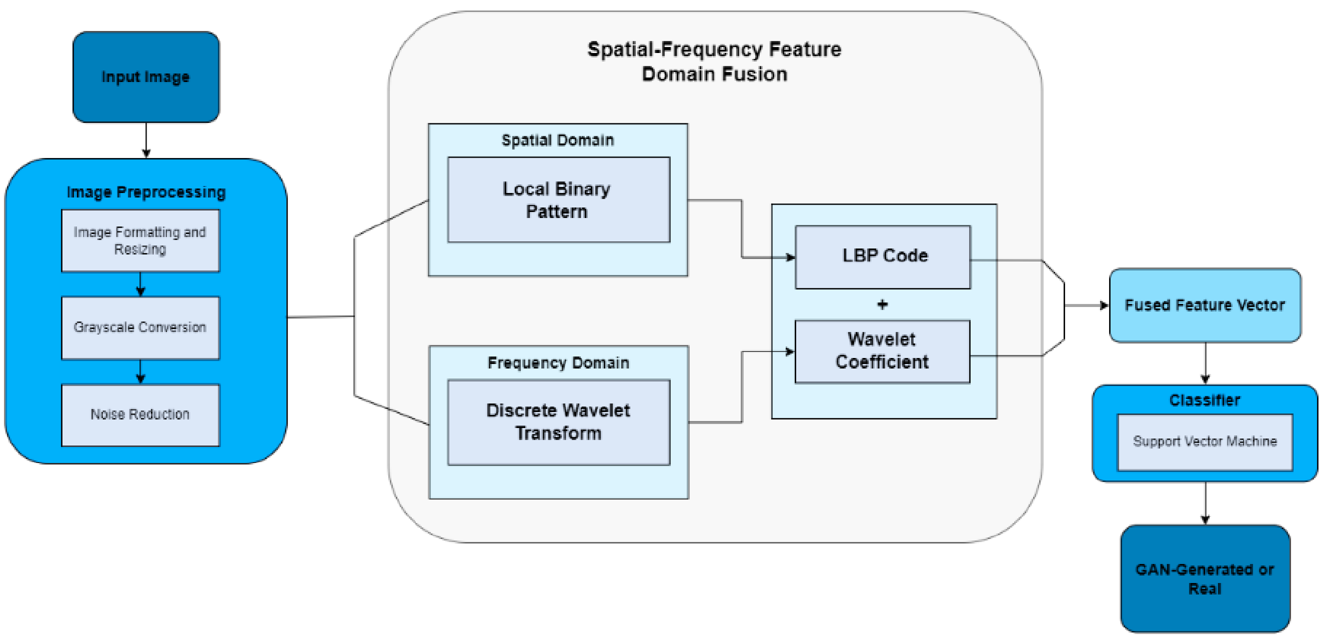
Classifier	Accuracy	Precision	Recall	F-Measure
SVM based on Spatial-Frequency Features (DWT & LBP)				

Table 4. Sample table for evaluating the accuracy of the proposed model in detecting GAN-generated images of different classes

Different Classes of GAN-generated images	Accuracy
Generated Faces	
Generated Animals	
Generated Objects	
Generated Scenes	

System Architecture:

Figure 6. System Architecture of the Detection of GAN-generated images using Spatial-Frequency Domain Fusion Data



1. Image Preprocessing

Aim of pre-processing is to improve the quality of the acquired images and enhance specific features relevant to further processing. The steps involved in pre-processing include:

1.1 Formatting and Resizing

Standardize the format and size of the acquired images to ensure consistency in the dataset. This may involve converting images to a specific file format and resizing them to a common resolution.

1.2 Grayscale Conversion

Convert the acquired images to grayscale representation if color information is not necessary for the analysis. Grayscale conversion simplifies the image data and reduces computational complexity.

1.3 Noise Reduction

This method was used to reduce unwanted noise or artifacts present in the acquired images. This can involve using filters such as median filtering, Gaussian filtering, or image denoising algorithms.

2. Feature Extraction

The feature extraction stage focuses on extracting meaningful information from the pre-processed images. This includes:

2.1 Frequency Domain

Discrete Wavelet Transform.

The Discrete Wavelet Transform (DWT) is a powerful technique for extracting information from images. The image is decomposed into a series of wavelet coefficients using DWT. These coefficients can then be used to represent an image in a more compact form.

The DWT will be utilized to get the wavelet coefficient of an image that will be represented as a frequency domain feature. To get the wavelet coefficient of an image:

- The DWT is applied to the preprocessed grayscale picture using the Haar wavelet function. This process decomposes the image into approximation coefficients, which represent low-frequency information, and detail coefficients, which represent high-frequency information, at different scales or levels.
- Both the approximation and detail coefficients generated from the DWT decomposition are chosen as characteristics for a more comprehensive analysis. All coefficients are included to ensure complete frequency information.
- For each image, the coefficients are flattened and merged into a feature vector. This feature vector is a compact representation of the picture that includes both low-frequency and high-frequency information recovered by the DWT.

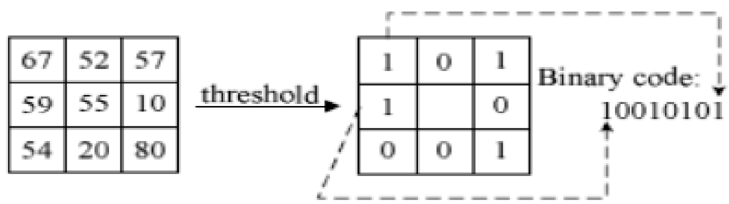
2.2 Spatial Domain

Local Binary Pattern.

LBP is a well-known and widely used feature extraction technique for many applications, including face recognition, fingerprint identification, and other classification problems.The LBP works in a block size of 3×3, in which the center pixel is used as a threshold for the neighboring pixel, and the LBP code of a center pixel is generated by encoding the computed threshold value into a decimal value.The LBP operator makes use of 8 pixels in a 3x3 pixel block, considering the center pixel as the threshold. The neighboring pixel is assigned value one if it has intensity

greater than the center pixel, else zero. The resulting ones and zeros are then concatenated in a particular order so as to generate the LBP code for the center pixel.

Figure 7: Illustration of Basic LBP operator



3. Feature Fusion

The features extracted from the frequency and spatial domains are combined using:

Feature Concatenation.

In the proposed study, feature concatenation involves merging the features extracted from spatial domain and frequency domain side by side to create a longer feature vector. Through feature concatenation, it can create a richer representation that incorporates multiple aspects of the data.

4. Classifier

Support Vector Machine.

The classifier component utilizes a Support Vector Machine (SVM) algorithm to classify the fused feature vectors. To perform the classification, The study will utilize the LIBSVM ,a tool library for SVM developed by Professor

ChihJen Lin in 2001, which can be used for data classification or regression. Since the focus of this study is to employ the combination of feature extraction as a single vector, there is no special requirement for the classification.

The classifier will be implemented to classify whether the image is GAN-generated or real based on extracted features.

Data Generation/Gathering Procedure

Pre-experimentation

Dataset Selection/Generation

In this step, the procedure focuses on selecting or generating a dataset that meets the desired criteria for the study. Several factors, including dataset size, diversity of images, and relevance, are considered. The datasets chosen should be of high quality, properly licensed, and suitable for use with GAN models.

Additionally, an evaluation of dataset adequacy is conducted to ensure that the desired total of 8,000 images, comprising both real and GAN-generated images, can be gathered. If the initially available dataset is insufficient to meet the required quantity or diversity, the procedure includes expanding the dataset through image generation using StyleGAN3. By utilizing StyleGAN3, synthetic images can be generated for each category, ensuring that the desired number of synthetic images is achieved and creating a diverse dataset.

Data Splitting

To create the training and testing sets, 70% of the total images will be allocated to the training set, with the remaining 30% assigned to the testing set. In this case, the training set will consist of 2,800 real images and 2,800 GAN-generated images from the 4,000 real images and 4,000 GAN-generated images. The remaining 1,200 real images and 1,200 GAN-generated images will be included in the testing set.

A separate training and testing approach will be carried out for each class to assess the model's performance. The initial 70% split ensures that each class's training set contains 70% of its generated and real images, resulting in 700 images. Similarly, each class's testing set will include 30% of the generated and real images, for a total of 300 images.

This approach allows focused evaluation of individual classes while maintaining consistency in training and testing set proportions. A full analysis of the model's performance across several classes can be obtained by first splitting the images into a general training and testing set, followed by a per-class evaluation based on the original split.

Training

During the training phase, the labeled images from the dataset are utilized to train the model. Before applying the proposed Spatial-Frequency feature fusion approach, the images undergo preprocessing steps to ensure consistency and enhance their suitability for analysis.

Once preprocessed, the images are then subjected to the Spatial-Frequency domain fusion data approach. This approach extracts and combines relevant spatial and frequency domain features, capturing the distinctive characteristics of GAN-generated images. The resulting fused features are fed into a Support Vector Machine (SVM) classifier, which is trained using the labeled training dataset.

Experimentation

In this phase, the performance of the trained classifier is evaluated based on a predefined experimental setup. The results of this testing phase are documented and analyzed in an experiment paper. A separate set of images, distinct from the training set, is utilized to assess the performance of the trained SVM classifier. The predicted labels are compared to the ground truth labels of the test set to determine the accuracy and performance of the classifier.

Post-experimentation

The results obtained from the experimentation are presented in the experiment paper, including performance metrics such as accuracy, precision, recall, and F1-score. These metrics provide quantitative measures of the effectiveness of the proposed spatial-frequency domain fusion approach in detecting GAN-generated images. Through a thorough analysis of the experiment's findings, valuable insights are gained regarding the approach's performance, potential applications, and areas for improvement. This phase concludes by summarizing the experiment's outcomes and providing recommendations for future research to advance the field of GAN-generated image detection.

Ethical Considerations

In the study titled "Detection of GAN-generated Images Using Spatial-Frequency Domain Fusion Data," it is crucial to establish research ethics first to protect participants and prevent potential harm.

The researchers will apply the principles of ethical considerations developed by Bryman and Bell (2019). The following steps will be taken in order to obtain the necessary approvals and protect the participants.

Prior to the study's involvement, a comprehensive research proposal outlining the study's objectives, methodology, potential risks, and measures to protect privacy will be submitted for ethical review. This process ensures that the study adheres to ethical standards and regulations.

To protect privacy and minimize harm, rigid measures will be implemented, such as protecting images that consist of faces and guaranteeing confidential data storage. The identities will be protected against unauthorized access or disclosure.

Data storage shall adhere to data protection laws and emphasize security with encryption and access controls to avoid loss or unauthorized access.

Concerns will be addressed through ongoing monitoring and ethical assessments, and open reporting will provide documentation of the study's procedures and ethical considerations. In this study, this guarantees safety and responsible knowledge progression.

Furthermore, affiliations of any kind, funding sources, and potential conflicts of interest shall also be disclosed. Finally, all communications related to this research shall be done with full integrity and transparency.

Data Analysis (Procedure and Treatment)

Statistical Treatment

The data will be subjected to particular procedures to meet the problem statement provided in the study. The following items are used to measure and assess the test results to determine the accuracy and significant difference in detecting GAN-generated images when using a mix of spatial and frequency features.

In this section, the researchers will use mathematical formulas for treatment of data to solve the statement of the problem indicated in this paper. The metrics below are used to quantify the result of the test's outcome. The following evaluations are carried out to assess the system's accuracy and significant difference in the following categories such as:

Precision, Recall, and F-measure

The following formula relating to the performance evaluation of the tool in detecting GAN-generated images when utilizing the combination of spatial and frequency data will be employed in computing the precision, recall, and f-measures.

Precision. It measures the accuracy of positive predictions made by the classifier. Analyzes the ratio of the tool's correct positive outputs. Precision is the percentage of the relevant instance found among the retrieved instances. A low false-positive rate is associated with high accuracy. That is, high precision determines how helpful the findings are.

Precision calculates the ratio of correctly detected GAN-generated images to the total number of images detected as GAN-generated by the tool. It measures the accuracy in detecting GAN-generated images without incorrectly identifying real images.

Equation 2. Formula for Precision

$$Precision = \frac{TP}{TP + FP}$$

Where:

True Positive (TP). If the actual input image is GAN-generated and the tool's predicted output is GAN-generated image.

False Positive (FP). If the actual input image is real and the tool's predicted output is GAN-generated.

Recall. This is the ratio of accurately predicted positive events. The recall factor compares the number of relevant examples retrieved with the account to the total number of appropriate instances. A high recall indicates that the classifier is making fewer false negative errors and indicates how complete the tool's results are.

Recall calculates the ratio of correctly identified GAN-generated images to the total number of GAN-generated images in the dataset. It indicates the tool's ability to identify GAN-generated images correctly.

Equation 3. Formula for Recall

$$Recall = \frac{TP}{TP + FN}$$

Where:

True Positive (TP). If the actual input image is GAN-generated and the tool's predicted output is GAN-generated image.

False Negative (FN). If the actual input image is GAN-generated and the tool's predicted output is real.

F-Measure. The weighted average of Precision and Recall.

Equation 4. Formula for Recall

$$F - Measure = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Achieving a high recall and precision during the performance evaluation of the tool indicates that the tool successfully identified the majority of the GAN-generated images. This implies that the tool accurately classified a significant portion of the samples and correctly identified nearly all of them.

A high F-measure indicates that the algorithm has achieved a good balance between precision and recall, meaning it has successfully identified a significant portion of the GAN-generated images (high recall) while minimizing false positives (high precision).

In other words, it implies that the algorithm accurately detected the majority of GAN-generated samples and correctly identified a large portion of them.

Accuracy

The researchers plan to assess the tool's performance to the measure of how closely the analysis results align with the actual values or ground truth.

Calculating the tool's accuracy entails determining the ratio of accurately predicted observations by the tool.

Accuracy measures the overall correctness of the tool's detection by calculating the ratio of correctly identified images to the total number of images.

Equation 5. Formula for Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

True Positive (TP). If the actual input image is GAN-generated and the tool’s predicted output is GAN-generated image.

False Negative (FN). If the actual input image is GAN-generated and the tool’s predicted output is real.

False Positive (FP). If the actual input image is real and the tool’s predicted output is GAN-generated.

True Negative (TN). If the actual input image is real and the tool’s predicted output is real.

Confusion Matrix

In the confusion matrix of spatial-frequency domain fusion data for detecting GAN generated images, true positives represent the correct detection of GAN-generated images as GAN-generated. True negative is evaluated when the software tool detects real images correctly as real. While, false positive means that real images are incorrectly detected as GAN-generated. Lastly, false negative is when the software tool incorrectly detects GAN-generated images as real.

Table 5. Confusion Matrix

		Actual	
		GAN-Generated Images	**Real Images**
Predicted	**GAN-Generated Images**	GAN-generated images correctly detected as GAN-generated	Real images incorrectly detected as GAN-generated
	Real Images	GAN-generated images incorrectly detected as Real	Real Images correctly detected as Real

References

A. D. Ningtyas E. B. Nababan S. Efendi (2022) Performance analysis of local binary pattern and k-nearest neighbor on image classification of fingers leaves http://dx.doi.org/10.22075/ijnaa.2022.5785

Aamir, M., Pu, Y. F., Rahman, Z., Tahir, M., Naeem, H., & Dai, Q. (2018, December 21). A Framework for Automatic Building Detection from Low-Contrast Satellite Images. Symmetry, 11(1), 3. https://doi.org/10.3390/sym11010003

Agarwal, H., & Singh, A. (2021). Deepfake Detection Using SVM. DOI: 10.1109/ICESC51422.2021.9532627

Akmalia, N., Sihombing, P., & Suherman. (2019). Skin Diseases Classification Using Local Binary Pattern and Convolutional Neural Network. 2019 3rd International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM). DOI:10.1109/elticom47379.2019.89438924

Anterpreet Kaur Bedi (2018) Local Binary Pattern Variants :A Review Anterpreet Kaur Bedi DOI: 10.1109/ICSCCC.2018.8703326

Aparna Goyal and Reena Gunja(2020) Bleeding Detection in Gastrointestinal Images using Texture Classification and Local Binary Pattern Technique https://doi.org/10.1051/e3sconf/202017003007

Aruraj, A., Alex, A., Subathra, M. S. ., Sairamya, N. ., George, S. T., & Ewards, S. E. V. (2019). Detection and Classification of Diseases of Banana Plant Using Local Binary Pattern and Support Vector Machine. 2019 2nd International Conference on Signal Processing and Communication (ICSPC). doi:10.1109/icspc46172.2019.8976

Cervantes, J. (2020). A comprehensive survey on support vector machine classification: Applications, challenges and trends. Knowledge-Based Systems, 199, 106044. doi:10.1016/j.knosys.2020.106044

Chandrasekaran, K. (2021, October 17). 2D-Discrete Wavelet Transformation and its applications in Digital Image Processing using MATLAB. Medium. https://medium.com/@koushikc2000/2d-discrete-wavelet-transformation-and-its-applications-in-digital-image-processing-using-matlab-1f5c68672de3

Creswell, A., White, T., Dumoulin, V., Arulkumaran, K., Sengupta, B., & Bharath, A. A. (2018). Generative Adversarial Networks: An Overview. IEEE Signal Processing Magazine, 35(1), 53–65. https://doi.org/10.1109/msp.2017.2765202

Cui, Y. (2020, March 17). No-Reference Image Quality Assessment Based on Dual-Domain Feature Fusion. Entropy, 22(3), 344. https://doi.org/10.3390/e22030344

Elmahdy, M.S., Abdeldayem, S.S. & Yassine, I.A. (2017). Low quality dermal image classification using transfer learning. Biomedical & Health Informatics (BHI) IEEE EMBS International Conference 2017: 373-376.

Gong, Y., & Farid, H. (2018). Image forensics: Recent advances and challenges. IEEE Signal Processing Magazine, 35(6), 119-133.

Gonzalez, R. C., & Woods, R. E. (2018). Digital image processing (4th ed.). Pearson Education.

Gornale, Basavanna M, and Kruthi R(2017) Fingerprint Based Gender Classification Using Local Binary Pattern-1S.S. Retrieved from: https://www.ripublication.com/ijcir17/ijcirv13n2_09.pdf

Hakimi, F., Hariri, M., & GharehBaghi, F. (2015, November). Image splicing forgery detection using local binary pattern and discrete wavelet transform. 2015 2nd International

Conference on Knowledge-Based Engineering and Innovation (KBEI). https://doi.org/10.1109/kbei.2015.7436195

Haseela H. A. (2022), Completed Local Binary Pattern with Random Forest on Image Classification, Retrieved from:https://ymerdigital.com/uploads/YMER210453.pdf

Huang, S., Cai, N., Pacheco, P. P., Narrandes, S., Wang, Y., & Xu, W. (2018). Applications of Support Vector Machine (SVM) Learning in Cancer Genomics. Cancer Genomics & Proteomics, 15(1), 41-51.

Jakkula, V. (n.d.). Support Vector Machines (SVM) Tutorial. Retrieved from https://course.ccs.neu.edu/cs5100f11/resources/jakkula.pdf

Karras, T., Laine, S., & Aila, T. (2019). A style-based generator architecture for generative adversarial networks. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 4401-4410).

Kaur, C. D., & Kanwal, N. (2019). An Analysis of Image Forgery Detection Techniques. Punjabi University, Patiala.

Kirvan, P. (March 2023). "Forensic Imaging." TechTarget. Retrieved from: https://www.techtarget.com/whatis/definition/forensic-image#:~:text=Forensic%20imaging%20is%20one%20element,backup%20software%20creates%20forensic%20images.

Kutlu, & Avcı. (2019, April 28). A Novel Method for Classifying Liver and Brain Tumors Using Convolutional Neural Networks, Discrete Wavelet Transform and Long Short-Term Memory Networks. Sensors, 19(9), 1992. https://doi.org/10.3390/s19091992

M. Wang, P. Zhao, X. Lu, F. Min and X. Wang, "Fine-Grained Visual Categorization: A Spatial–Frequency Feature Fusion Perspective," in IEEE Transactions on Circuits and Systems *for Video Technology, vol. 33, no. 6, pp. 2798-2812, June 2023, doi: 10.1109/TCSVT.2022.3227737.*

Mahale, V. H., Ali, M. M. H., Yannawar, P. L., & Gaikwad, A. T. (2017). Image Inconsistency Detection Using Local Binary Pattern (LBP). Procedia Computer Science, 115, 501–508. doi:10.1016/j.procs.2017.09.097

Manish Shankar Kaushik, Rabul Saikia, Dr. Aditya Bihar Kandali (2019) Digital Image Forgery Detection using Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG)

McCloskey, S., & Albright, M. (2019). Detecting GAN-Generated Imagery Using Saturation Cues. 2019 IEEE International Conference on Image Processing (ICIP). doi:10.1109/icip.2019.8803661

Michael Goebel, Lakshmanan Nataraj, Tejaswi Nanjundaswamy, Tajuddin Manhar Mohammed, Shivkumar Chandrasekaran, B.S. Manjunath (20 July 2020) Detection, Attribution and Localization of GAN-Generated Images DOI:10.2352/ISSN.2470-1173.2021.4.MWSF-276

Narin Aslan, Sengul Dogan, Gonca Ozmen Koca(2022) Covid-19 X-ray image classification using SVM based on Local Binary Pattern-Classification of Chest X-ray https://doi.org/10.55525/tjst.1092676

Nataraj, L., Mohammed, T. M., Chandrasekaran, S., Flenner, A., Bappy, J. H., Roy-Chowdhury, A. K., & Manjunath, B. S. (2019, October 3) Detecting GAN generated Fake Images using Co-occurrence Matrices. Retrieved from arXiv preprint arXiv:1910.01673. https://doi.org/10.48550/arXiv.1903.06836

Nataraj, L., Mohammed, T. M., S, M. B., Chandrasekaran, S., Flenner, A., Bappy, Jawadul H, & Roy-Chowdhury, Amit K. (2019). Detecting GAN generated Fake Images using Co-occurrence Matrices. ArXiv.org. https://arxiv.org/abs/1903.06836

Pan, Y., Zhang, Y., Wei, Y., & Liu, Q. (2019). Saliency detection based on the fusion of spatial and frequency domain analysis. 2019 3rd International Conference on Electronic Information Technology and Computer Engineering (EITCE). doi:10.1109/eitce47263.2019.9095064

Pupale, R. (2018) Support Vector Machines(SVM) — An Overview. Retrieved from https://towardsdatascience.com/https-medium-com-pupalerushikesh-svm-f4b42800e989

R. A. Asmara, R. Romario, K. S. Batubulan, E. Rohadi, I. Siradjuddin, F. Ronilaya, R.Ariyanto, C. Rahmad and F. Rahutomo (2018) Classification of pork and beef meat images using extraction of color and texture feature by Grey Level Co-Occurrence Matrix method DOI 10.1088/1757-899X/434/1/012072

Ribas. LC, Sa. JJDS, Scabini. LFS, Bruno. OM,(2020) "Fusion of complex networks and randomized neural networks for texture analysis," Pattern Recognit., vol. 103, UNSP: 107189, Jul. 2020.

Shaham, T. R., Dekel, T., & Michaeli, T. (2019). SinGAN: Learning a Generative Model From a Single Natural Image. Openaccess.thecvf.com. https://openaccess.thecvf.com/content_ICCV_2019/html/Shaham_SinGAN_Learning_a_Generative_Model_From_a_Single_Natural_Image_ICCV_2019_paper.html

Shamsul J. Elias, Shahirah Mohamed Hatim, Nur Anisah Hassan, Lily Marlia Abd Latif, R. Badlishah Ahmad, Mohamad Yusof Darus, Ahmad Zambri Shahuddin(2019) Face recognition attendance system using Local Binary Pattern (LBP) DOI: 10.11591/eei.v8i1.1439

Srivastava, M., Siddiqui, J., & Ali, M. A. (2020). Local Binary Pattern based Technique for Content Based Image Copy Detection. 2020 International Conference on Power Electronics & IoT Applications in Renewable Energy and Its Control (PARC). doi:10.1109/parc49193.2020.236629

Subramaniam, Jalab, Ibrahim, & Mohd Noor. (2019, November 10). Improved Image Splicing Forgery Detection by Combination of Conformable Focus Measures and Focus Measure Operators Applied on Obtained Redundant Discrete Wavelet Transform Coefficients. Symmetry, 11(11), 1392. https://doi.org/10.3390/sym11111392

Sun, Deng, Liu, & Deng. (2019, November 30). Combination of Spatial and Frequency Domains for Floating Object Detection on Complex Water Surfaces. Applied Sciences, 9(23), 5220. https://doi.org/10.3390/app9235220

T. Ojala, M. Pietikäinen, and T. Maenpaa(2002), "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 971–987,

Tang, G., Sun, L., Mao, X., Guo, S., Zhang, H., & Wang, X. (2021). Detection of GAN-Synthesized Image Based on Discrete Wavelet Transform.

Tang, G., Sun, L., Mao, X., Guo, S., Zhang, H., & Wang, X. (2021, June 15). Detection of GAN-Synthesized Image Based on Discrete Wavelet Transform. Security and Communication Networks, 2021, 1–10. https://doi.org/10.1155/2021/5511435

Thakur, T., Singh, K., & Yadav, A. (2018). Blind Approach for Digital Image Forgery Detection. In M.Tech Department of Computer Technology, YCCE, Nagpur, Maharashtra, India.

Liu, B., Yang, F., Bi, X., Xiao, B., Li, W., & Gao, X. (2022). Detecting Generated Images by Real Images. Lecture Notes in Computer Science, 95–110. https://doi.org/10.1007/978-3-031-19781-9_6

Wang, R., Juefei-Xu, F., Ma, L., Xie, X., Huang, Y., Wang, J., & Liu, Y. (2020). FakeSpotter: A Simple yet Robust Baseline for Spotting AI-Synthesized Fake Faces. ArXiv:1909.06122 [Cs]. https://arxiv.org/abs/1909.06122

Xiaofeng Fu Wei Wei Centralized Binary Patterns Embedded with Image Euclidean Distance for Facial Expression Recognition https://doi.org/10.1109/ICNC.2008.94

Xu Zhang, Svebor Karaman, and Shih-Fu Chang (15 October 2019) Detecting and Simulating Artifacts in GAN Fake Images DOI: 10.1109/WIFS47025.2019.9035107

Yang, J., Gong, D., Liu, L., & Shi, Q. (2018). Seeing Deeply and Bidirectionally: A Deep Learning Approach for Single Image Reflection Removal. Openaccess.thecvf.com. https://openaccess.thecvf.com/content_ECCV_2018/html/Jie_Yang_Seeing_Deeply_and_ECCV_2018_paper.html

Zhang, H., Qu, Z., Yuan, L., & Li, G. (2017). A face recognition method based on LBP feature for CNN. Advanced Information Technology, Electronic and Automation Control Conference (IAEAC) 2: 544-547.

Zhou, R. (2014). Spatial and Frequency Domain–Based Feature Fusion Method for Texture Retrieval. Intelligent Data Analysis and Its Applications, Volume I, 257–265. https://doi.org/10.1007/978-3-319-07776-5_27

Appendices

Appendix 1: Instrument

Experiment Paper of Detection of GAN-generated Images Using Spatial-Frequency Domain Fusion Data

Objectives:

To use the tool, and detect an image as fake or real, and to know if the proposed method has an impact on the performance of the detection tool.

Materials and/or Equipment:

1. **Development of the Detection Tool:** The developed tool implementing the proposed method which is detection of GAN-generated images using spatial-frequency domain fusion data.
2. **Acquisition of Real and Fake Images**: A dataset of images containing both real and GAN-generated images must be acquired.
3. **Experimental Procedure:** The acquired images must be processed using the developed detection tool. The tool extracts spatial-frequency domain features from the images and fuses them to form a comprehensive representation. A classification algorithm must be applied to classify the images as either real or fake.
4. **Performance Evaluation:** The performance of the detection tool must be evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The results will be compared with baseline methods for GAN-generated image detection to assess the impact of the proposed method.

Procedure:

1. Researchers should prepare the experiment paper which will be evaluated using the developed tool, implementing the proposed technique for detecting GAN-generated images.
2. The tool will undergo multiple trials to assess its performance.
3. The researchers will assess how accurate the output of the tool is with the actual assessment of detecting GAN-generated images.
4. The "Evaluation" column will be filled out by selecting one of the following options:

    - **True Positive (TP).** If the actual input image is GAN-generated and the tool's predicted output is GAN-generated image.

    - **False Negative (FN).** If the actual input image is GAN-generated and the tool's predicted output is real.

    - **False Positive (FP).** If the actual input image is real and the tool's predicted output is GAN-generated.

    - **True Negative (TN).** If the actual input image is Real and the tool's predicted output is real.

Table 2: Sample Table for evaluating the tool developed in detecting GAN-generated images

Image	Expected Result	Actual Result	Evaluation

Table 3: Sample Table for testing the accuracy, precision, recall and f1-measure implementing the proposed approach

Classifier	Accuracy	Precision	Recall	F-Measure
SVM based on Spatial Domain (LBP) and Frequency Domain (DWT) Fusion Data				

Table 4. Sample table for evaluating the accuracy of the proposed model in detecting GAN-generated images of different classes

Different Classes of GAN-generated images	Accuracy
Generated Faces	
Generated Animals	
Generated Objects	
Generated Scenes	

Observation:

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Conclusion:

Recommendation:

Appendix 2: Letter of Permission to Conduct the Study

Polytechnic University of the Philippines

College of Computer and Information Sciences
Department of Computer Science

Manila, Philippines

Subject: Request for Permission to Conduct Research Study

Dear Ma'am/Sir,

This is to seek your permission to conduct a research study as part of our thesis titled "**Detection of Gan Generated Images Using Spatial-Frequency Domain Fusion Data."** We are currently a Third Year Computer Science student at College of Computer and Information Sciences under the guidance of Mr. Michael B. Dela Fuente.

The purpose of the study is to evaluate the effectiveness of spatial-frequency feature fusion. In light of the nature of the study, we gladly ask your permission to access and gather pertinent data from institution given the nature of the study. The following actions will be part of the data collection:

1. Examining and examining publicly accessible image datasets for images produced by GAN.
2. Experimenting with visual data extraction in the spatial-frequency domain.
3. Using several analysis and detection methods to GAN-generated picture analysis.
4. Preserving the data's privacy and confidentiality throughout the study.

Please find attached research proposal stating the objectives, methodology, and expectedd outcomes of the study attached. We are also available to respond to any questions you might have about the study or to offer any further information.

We appreciate your suggestions and time. We eagerly look forward to your favorable response.

Sincerely,

Gallardo, Matthew
Martinez, Danniel P.
Nebrida, Carryl Cassandra J.
Pangilinan, Patrick F.

Appendix 3: Biographical Statement

Matthew Gallardo was born on September 8, 2001 in Quezon City. He is currently a 3rd year student at Polytechnic University of the Philippines taking the program of Bachelor of Science in Computer Science. He is currently a scholar in the Commission on Higher Education (CHED) and Quezon City Youth Development. He is knowledgeable in various tools and programming languages like C, Java , JavaScript, Python and Git. His expertise lies in web development, with a particular focus on backend development. He is passionate about optimizing the functionality and efficiency of software and websites.

Danniel Martinez was born on June 4, 2002 in Antipolo City. He is a third-year student at the Polytechnic University of the Philippines, where he is studying computer science. He is now pursuing two scholarships in his province: the RCSP (Rizal College Student Program) and the EAP-Antipolo Scholarship Program. He is well-versed in a number of programming and user interface design tools, including Figma and Visual Studio Code. He is fluent in a number of programming languages, including C, Python, and web design languages like HTML, CSS, and Javascript. His specialty is in front-end development, particularly website development.

Carryl Cassandra J. Nebrida was born on September 22, 2002 in Pangasinan. She is currently a 3rd year student at Polytechnic University of the Philippines taking the program of Bachelor of Science in Computer Science. She is knowledgeable in various fields such as Visual Basic, Java, C, Python, Web Development. She is also familiar with various tools like Figma and Visual Studio Code. Her documentation and UI/UX Design skills are also proven good as she is often the head of every project's interface.

Patrick F. Pangilinan was born on March 15, 2002 in Nueva Ecija. He currently resides in Sta. Mesa, Manila. He is studying a Bachelor of Science in Computer Science at the Polytechnic University of the Philippines. He is knowledgeable in different programming languages like C, Java, Python, and various tools like Figma and VsCode. With a keen eye for detail, he excels in creating comprehensive and well-structured documentation that is both informative and accessible.

Screen Design / Mock-up

Figure 8. Home Page

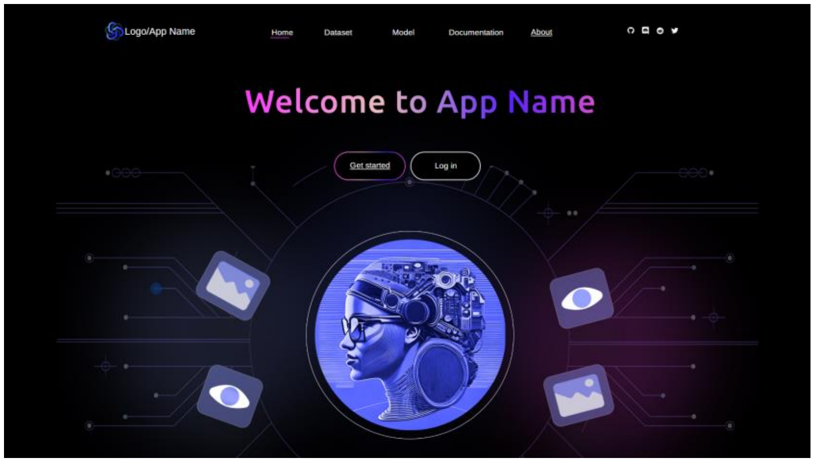

Figure 9. About Page

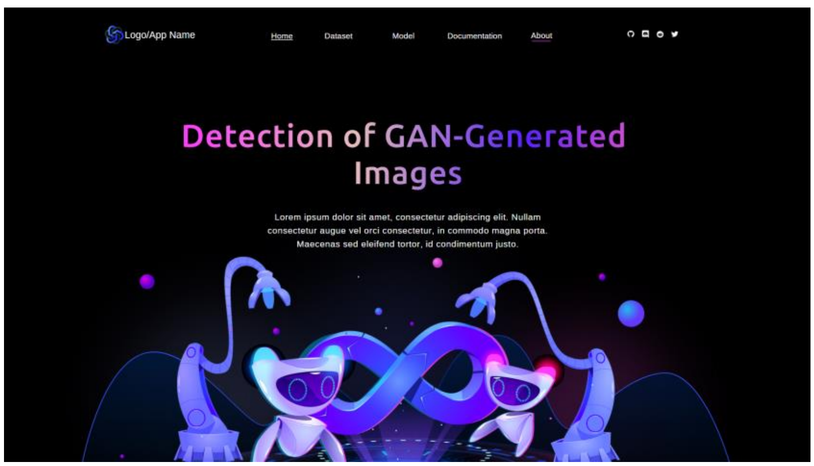

Figure 10. Result Page