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# VISUAL RESURGENCE - IMAGE RESTORATION ON CRIMINAL IMAGERY

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*Abstract*— **This project focuses on complex processing approaches to address typical problems in low-resolution images, with the goal of improving criminal imagery through an advanced image restoration pipeline. Distortions that are specifically targeted include cracks, scratches, aging effects, and resizing artifacts. The initiative systematically enhances image quality by utilizing cutting-edge image restoration algorithms, which recreate and amplify visual information for forensic investigation by law enforcement.**

**The methodology acknowledges the difficulties in managing many forms of distortions within a single image and takes a thorough approach to handling them. By avoiding the addition of artificial components, the restoration method is intended to maintain the authenticity of facial features. The ramifications are profound, providing investigators with a better knowledge of facial features and facilitating criminal identification through sharper, more detailed photos. The initiative has the potential to enhance facial recognition system matches and raise the bar for forensic analysis as a whole. In conclusion, this study describes a complex method of picture enhancement and emphasizes how it can help law enforcement with criminal investigations by giving them better, more readable photos for in-depth forensic examination.**

***Keywords***— Image Restoration, Generative Adversarial Networks, Criminal Mugshots, Data Preprocessing, Deep Learning.

## I. INTRODUCTION

Criminal mugshots are essential to law enforcement in identifying and apprehending those engaged in criminal activity. Unfortunately, there are a number of reasons why the quality of these photos is frequently lowered, including inadequate illumination, camera restrictions, and natural noise. To tackle these issues and improve the investigative value of criminal mugshots, this work investigates the use of sophisticated picture restoration methods, namely Generative Adversarial Networks (GANs).

The dataset that is being studied is a sizable collection of 70,008 front-facing photos that have been matched with matching side-facing photos, each of which represents a different prisoner. An extensive depiction of people involved in the criminal justice system is offered by this vast dataset. Notably, 69,827 of these inmates had corresponding descriptors related to their sex, height, weight, race, eye colour, hair colour, and kind of offence committed.

The dataset is carefully preprocessed in order to set it up for successful image restoration. The following five important factors are taken into account: resizing, noise reduction, oldify effects, black and white conversion and scratches removal. With a methodical division of the dataset into subsets, 11,668 images are obtained for every preprocessing characteristic. A thorough examination of the effects of each preprocessing step on the overall image restoration process is made possible by this strategic split.

In the realm of picture restoration, the application of Generative Adversarial Networks is a cutting-edge strategy. GANs, which are composed of a discriminator network and a generator network, work together to produce high-quality images from inputs that are deemed degraded. The discriminator network functions as a binary classifier, and the generator network is responsible for creating restored or improved images. Its job is to discern between artificially manufactured and repaired photos and actual, high-quality images. This adversarial approach guarantees that the recovered images are genuine and of excellent quality in addition to improving the generator's capacity to generate realistic outputs.

This study investigates the use of ESRGAN, BSRGAN, SWINIR, GFPGAN and NoGAN to improve the accuracy and consistency of criminal mugshot analysis. Our goal is to give law enforcement agencies strong tools for more reliable and accurate criminal investigations through creative GAN designs, rigorous preprocessing, and an extensive training regimen. The experimental findings and conversations that follow provide insightful information about the efficacy of our strategy and further the ongoing advancement of forensic technology.

A. OBJECTIVES

This research project's main goal is to improve the quality of criminal mugshots by utilising cutting-edge picture restoration techniques, particularly Generative Adversarial Networks (GANs).

*Improve Visual Detail and Clarity*: Improving the mugshots of criminals' visual clarity and detail is the main objective. The project intends to lessen the effects of different picture degradations by employing state-of-the-art methods like GANs. This will give law enforcement more accurate and insightful representations of the subjects for identification and investigation.

*Intense Dataset Examination*: Conduct a comprehensive examination of the dataset, delving into the various attributes of the criminal justice system. To comprehend the scope of the dataset and its consequences for picture restoration, the study looks at labels related to sex, height, weight, race, hair colour, and eye colour.

*Optimise Preprocessing Techniques*: Put into practice a preprocessing plan that includes the following six essential elements: resizing, noise reduction, oldify effects, crack handling, black and white conversion, and scratches removal. With an awareness of how various preprocessing methods affect the ultimate quality of the restored photos, the research aims to optimise these methods in order to efficiently prepare the dataset for further image restoration.

*Methodical Dataset Division*: Produce 11,668 images for every preprocessing characteristic by methodically dividing the dataset into subgroups. This section enables a thorough examination of the efficiency of every preprocessing step and facilitates comprehension of the complex roles played by these features in the overall image restoration procedure.

*Implement GAN Architecture*: Make use of Generative Adversarial Networks' capabilities to restore crime scenes. The research will specifically concentrate on the development and optimisation of the GAN architecture, which consists of a discriminator network and a generator network, in order to produce high-quality images from inputs that have been degraded.

*Improve Training Process*: Create and improve the GANs' training procedure to make sure the generator network gains the ability to generate realistic, high-quality images. To attain ideal outcomes for picture restoration, the adversarial training procedure must be balanced.

*Quantitative and Qualitative Evaluation*: Use quantitative measures like the Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) to assess how well the picture restoration procedure worked. Do qualitative evaluations as well to make sure the recovered photos are accurate and realistic in addition to meeting quality standards.

*Analysis of Preprocessing Impact*: Examine and evaluate the experimental data to learn how various preprocessing characteristics affect the Generative Adversarial Networks' overall performance. Determine any obstacles or restrictions and make suggestions for possible upgrades or remedies.

*Contribute to Forensic Technologies*: By giving law enforcement organisations an improved instrument for criminal identification, you may help forensic technologies progress. Providing investigators with improved, detailed visuals to aid in precise decision-making is the goal.

*Future Optimisation and Application*: Suggest avenues for further study to improve GAN design, investigate new preprocessing methods, and enlarge the dataset. Think about possible partnerships with law enforcement organisations to test and apply the proposed image restoration technique in practical contexts.

## II. LITERATURE REVIEW

[1] The groundwork for image-to-image translation challenges was laid by Isola and colleagues with their introduction of conditional GANs. This groundbreaking effort is especially important since it supports the goal of using labelled data to restore criminal mugshots. A useful paradigm for improving image quality and realism is introduced by the idea of conditioning GANs on particular attributes.

[2] This paper introduces SRGAN, the first framework capable of generating photo-realistic natural images at 4x upscaling factors. By utilizing a generative adversarial network (GAN), SRGAN incorporates a perceptual loss function comprising adversarial and content losses. The adversarial loss aligns the generated images with the natural image manifold, while the content loss emphasizes perceptual similarity. Evaluation through mean-opinion-score (MOS) tests shows significant improvements in perceptual quality compared to state-of-the-art methods, with SRGAN achieving MOS scores closer to those of original high-resolution images.

[3] The paper explores the evolution of image denoising from classical approaches to modern deep learning-based methods. It discusses the resurgence of interest in denoising due to advancements in deep learning, highlighting the synergy between traditional techniques and DL-

based alternatives. Additionally, it delves into the expanded scope of denoising applications, such as solving inverse problems and supporting diffusion-based image synthesis. The survey aims to provide a comprehensive overview of the history of image denoising, shedding light on recent developments and the transformative impact of deep learning in this domain.

[4] The literature review presents a novel loss function, Wing loss, for robust facial landmark localization using Convolutional Neural Networks (CNNs). It evaluates and compares various loss functions, highlighting the need for attention to small and medium-range errors in CNN-based models. The Wing loss amplifies the impact of errors within a specified interval, addressing shortcomings in existing loss functions. Additionally, a pose-based data balancing strategy is proposed to tackle the under-representation of samples with large out-of-plane head rotations. Experimental results on AFLW and 300W datasets demonstrate the effectiveness of the Wing loss and the proposed method over state-of-the-art approaches.

[5] A thorough analysis of image quality measurements, including the Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index (SSIM), was provided by Wang and his co-authors. To ensure a reliable assessment of image quality, it is imperative to comprehend these metrics for the proposed project's quantitative assessment of restored criminal mugshot photographs.

[6] The literature review discusses a method for extracting facial expression information using Gabor filters. These filters are applied in a multi-orientation, multi-resolution manner and aligned approximately with the face. The resulting similarity space is compared with human-rated semantic expressions. The study demonstrates the feasibility of constructing a facial expression classifier using Gabor coding. Moreover, the Gabor representation exhibits psychological plausibility, crucial for human-computer interfaces. This highlights the potential utility of Gabor filters in analyzing facial expressions across various applications.

[7] The paper proposes a novel residual dense network (RDN) for image super-resolution (SR) using deep convolutional neural networks (CNNs). It addresses the challenge of underutilized hierarchical features in deep CNN-based SR models by introducing residual dense blocks (RDBs) for effective feature extraction and fusion. The RDN achieves superior performance compared to state-of-the-art methods on benchmark datasets, demonstrating the efficacy of its architecture in enhancing image SR.

[8] Progressive growth of GANs is introduced in the study by Karras and collaborators, offering a novel method for training GANs gradually. Modern GAN architectures are discussed in this paper, which may help optimise the GAN that is suggested for the project and guarantee better stability and quality of picture restoration.

## III.EXISTING SYSTEM

### A. EXISTING METHOD

The state-of-the-art approaches used today for criminal mugshot image restoration mostly rely on conventional image processing algorithms and straightforward interpolation techniques. To improve image quality, these techniques frequently use fundamental techniques like denoising filters, histogram equalisation, and simple interpolation algorithms. Furthermore, certain systems might use rule-based techniques for particular preprocessing jobs, like crack or scratch removal.

### A. LIMITATIONS

Even with their use in forensic applications, current techniques for restoring criminal mugshot images have a number of drawbacks:

*Restricted Restoration Capability*: Conventional techniques frequently lack the expertise necessary to successfully recover intricate image degradations, leading to less than ideal results, particularly when there is a lot of noise, scratches, or other artefacts.

*Requirements for Manual Preprocessing*: A lot of the current systems can need manual assistance with some preprocessing operations. For example, manually recognising and labelling scratches or cracks can be error-prone and time-consuming.

*Generic Approach*: Conventional techniques frequently use a generic approach without taking into account the unique qualities of each image. Because the same restoration procedures are used everywhere, regardless of the distinctive qualities found in every criminal mugshot, this could result in less than ideal results.

*Incapacity to Learn Complex Patterns*: Complex patterns and structures found in the data cannot be learned using traditional approaches. Because of this, people could find it difficult to adjust to the variety seen in criminal mugshot photos, particularly when dealing with uneven lighting or a range of expressions on the face.

*Inadequate Preprocessing Management*: Preprocessing techniques like noise reduction and scratch removal may be poorly managed and underutilised for criminal mugshot photos. This may lead to an insufficient restoration or inadvertent changes to the image.

*Dependency on Manual Image Labelling*: Some supervised learning techniques may mainly rely on manual image labelling, which can be resource-intensive and impractical when working with big datasets.

Given these constraints, it is evident that sophisticated picture restoration methods are required in order to get over these obstacles and give law enforcement automated, automated, and more precise instruments for criminal identification and investigation. To overcome these drawbacks and improve the calibre of recovered criminal mugshot photos, the suggested approach incorporates deep learning, most especially Generative Adversarial Networks (GANs).

## IV.PROPOSED SYSTEM

### A. PROBLEM IDENTIFICATION

The identification of issues pertaining to the processing and restoration of criminal mugshot images shows obstacles that impede the effectiveness and precision of forensic analyses. The issues listed below have been determined:

*Poor Image Quality*: Noise, scratches, and distortions are just a few of the natural deteriorations that criminal mugshot photos frequently experience. The low quality of these photos makes it more difficult for law enforcement to conduct precise and trustworthy identification.

*Drawbacks of conventional methods*: The effectiveness of traditional image processing techniques like denoising and interpolation in restoring criminal mugshot photos is limited. These techniques frequently fall short of handling the intricate patterns of deterioration shown in forensic photos.

*Manual Intervention in preprocessing*: Preprocessing tasks in existing systems, such as scratch removal or attribute labelling, may need to be done by hand. Large datasets may not be scalable due to the time-consuming and error-prone nature of this human labour.

*Inability to Adjust to Varying Image Conditions*: Conventional methods are not able to adjust to the many conditions that are present in criminal mugshot photographs. For a strong and flexible picture restoration system, it is necessary to overcome the obstacles posed by variations in lighting, facial expressions, and other elements.

*Complex Patterns and Structures*: Traditional approaches find it difficult to accurately learn and reproduce the complex patterns and structures that are frequently seen in criminal mugshots. To create realistic restorations, complex procedures are needed due to variances in facial features, occlusions, and non-uniform lighting conditions.

*Challenges with Quantitative Evaluation*: It is difficult to gauge the effectiveness of image restoration procedures in an objective manner due to the lack of standardised quantitative evaluation measures for evaluating the quality of restored images. The creation and optimisation of restoration algorithms may be hampered by this lack of measures.

*Difficulties in Forensic Image Analysis*: The validity and precision of criminal mugshot photos present difficulties for the larger field of forensic image analysis. The credibility of forensic practices is compromised by ineffective restoration methods that hinder the identification and investigation processes.

*Ethical Issues*: Using picture restoration technology in criminal investigations brings up ethical issues. Forensic techniques must respect ethical principles and preserve public trust by guaranteeing fairness, accountability, and transparency in the restoration process.

### B. BLOCK DIAGRAM

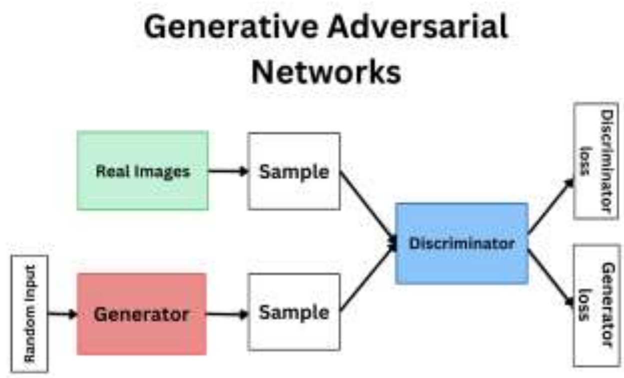


Fig.1.Working of Generative Adversarial Networks

Figure 1 illustrates the operation of a Generative Adversarial Network (GAN). The Generator tries to produce a high-quality image, while the Discriminator possesses a set of high-quality images. The Discriminator's role is to identify differences between the high-quality reference image and the generated image. In the event of the Discriminator detecting a difference, it results in a Generator loss, prompting the need for regeneration. Conversely, if no difference is detected, it leads to a Discriminator loss, signifying the inclusion of the image in the output.

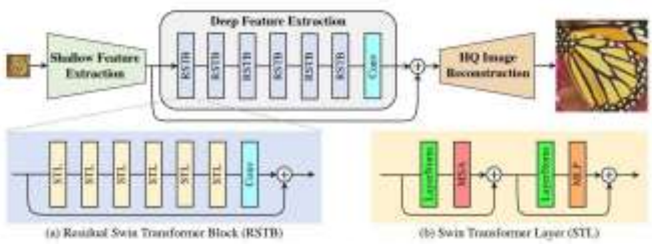


Fig.2 .Architecture of SWINIR for Image Restoration

Figure 2 illustrates the architecture of SWIN IR, a deep learning model based on the Swin Transformer for image restoration tasks. SWIN IR achieves cutting-edge results on a range of image restoration tasks, such as JPEG compression artifact reduction, image super-resolution, and image denoising . Shallow Feature Extraction module concentrates on low-frequency data to extract fundamental features from the input image using a convolutional layer. Using multiple Residual Swin Transformer Blocks (RSTB), Deep Feature Extraction module is the central function of SWIN IR. Effective high-level feature extraction is made possible by each RSTB's use of multiple Swin Transformer layers for local picture patch analysis and relationship analysis.High-Quality Image Reconstruction module reconstructs a high-quality image by combining the shallow and deep characteristics.

C. METHODOLOGY

The Generative Adversarial Network (GAN) architecture used by ESRGAN, or Enhanced Super-Resolution Generative Adversarial Network, consists of a generator and discriminator. The discriminator assesses the realism of the high-resolution images created by the generator from their low-resolution equivalents. Using paired datasets, training entails minimising adversarial loss and pixel-wise mean squared error. High-level features are captured by perceptual loss, which is frequently included. Residual blocks are adopted by ESRGAN in order to improve architecture. Steps in post-processing could come next to further improve outcomes. ESRGAN is particularly effective at producing aesthetically pleasing high-resolution images, which is why it is frequently used for tasks like image enhancement and upscaling. After it is trained, the model makes it easier to produce high-quality photos from low-resolution inputs that have never been seen before.

This study presents a more complex and useful degradation model to solve the shortcomings of single image super-resolution (SISR) approaches when real images deviate from expected degradation models. With the goal of better covering the wide range of real-world image degradations, the suggested model incorporates noise degradations, downsampling, and randomly shuffled blur. Isotropic and anisotropic Gaussian kernels are used in the blur component, and random selection from closest, bilinear, and bicubic interpolations is used in the downsampling process. The noise component is created by combining different Gaussian noise levels, integrating JPEG compression at various quality factors, and processing camera sensor noise using a RAW image noise model and a reverse-forward camera image signal processing (ISP) pipeline model. In order to evaluate the performance of this new degradation model, real and synthetic pictures with a range of degradations are enhanced using a deep blind ESRGAN super-resolver that has been developed. Based on experimental results, the model can greatly improve the usability of deep super-resolvers and provide a reliable stand-in for SISR applications in the real world.

Recent image restoration techniques such as SwinIR differ from conventional convolutional neural networks in that they make use of the Swin Transformer architecture. In contrast to traditional CNNs, SwinIR produces outstanding results by effectively capturing complex attention interactions between picture patches. Shallow feature extraction, deep feature extraction, and high-quality picture reconstruction are the three main parts of the approach. Many residual Swin Transformer blocks (RSTB), each including Swin Transformer layers with a residual connection, are used by the deep feature extraction module. Experiments on three major tasks—JPEG compression artefact reduction, image denoising (including grayscale and colour image denoising), and image super-resolution (including classical, lightweight, and real-world scenarios)—showcase the superiority of SwinIR over state-of-the-art techniques. Its usefulness is demonstrated in a variety of picture restoration applications, as it achieves performance gains of up to 0.14~0.45dB across varied jobs.

GFPGAN, short for Generative Facial Prior GAN, revolutionizes the enhancement and restoration of low-quality facial images through its innovative architecture. At its core lies the utilization of StyleGAN, a pre-trained facial Generative Adversarial Network (GAN), as a generative facial prior (GFP), imbuing the system with a wealth of knowledge on realistic and high-quality facial features. The process begins with the Degradation Removal Module, employing a U-Net architecture to eliminate noise, artifacts, and blurriness from the input image. Crucially, the incorporation of the GFP is facilitated by Channel-Split Spatial Feature Transform (CS-SFT) layers, which dissect extracted features into distinct channels, allowing focused processing on specific facial aspects. The subsequent Latent Code Mapping stage transforms these processed features into a latent code suitable for StyleGAN, acting as a bridge between the degradation removal module and the face generation process. Finally, StyleGAN generates a high-resolution image that seamlessly integrates the enhanced features while preserving the original image's structural integrity. GFPGAN excels in balancing realism and fidelity, achieving image enhancement in a single forward pass, thus demonstrating remarkable efficiency and effectiveness in facial image restoration and enhancement tasks.

NoGAN is a new kind of GAN training to address a few major issues with the DeOldify model that existed before. It offers the advantages of GAN training with less time spent on actual GAN training. Rather, the majority of training time is devoted to pretraining the generator and critic independently using more straightforward, dependable, and quick conventional techniques. One important takeaway from this is that, in general, the more "conventional" approaches provide the majority of the desired outputs, and that GANs can be employed to bridge the realism gap. In addition to gaining the complete realistic colorization capabilities that previously required days of gradually resizing GAN training, the generator also gains nearly all of the other undesirable side effects of GANs during the extremely brief actual GAN training period. Depending on your method, you can actually almost completely remove bugs and artifacts. This is a new technique, as far as I'm aware. It's also really successful.

## V.RESULTS AND DISCUSSIONS

Fig.3.Output of ESRGAN,BSRGAN and SWINIR

The distinct characteristics of ESRGAN, BSRGAN, and SwinIR in the context of image restoration have been thoroughly examined. ESRGAN emerged as a formidable contender, showcasing unparalleled excellence in high-resolution upscaling tasks, particularly at scales beyond x4. The generated images exhibited an impressive level of detail and sharpness. However, challenges were encountered in more intricate scenes, where artifacts occasionally surfaced, and difficulties arose in preserving realistic textures, particularly evident in the nuanced nuances of portraits.

BSRGAN, on the other hand, demonstrated a specialized proficiency in restoring details within portrait images. Its ability to handle facial features and textures with finesse resulted in outcomes that not only restored but enhanced the natural characteristics of the subjects. Nonetheless, it should be noted that BSRGAN might not match the same level of sharpness as ESRGAN in more generalized upscaling tasks, making it less suitable for scenarios involving landscapes or abstract imagery.

SwinIR, characterized by its versatility, showcased robust performance across a spectrum of restoration tasks. It excelled not only in super-resolution but also in denoising and JPEG artifact removal. The model consistently achieved state-of-the-art results, presenting a harmonious balance between sharpness and naturalness. However, it was noted that SwinIR, while highly effective, came with a higher computational cost compared to ESRGAN and BSRGAN, requiring additional resources for processing.

GFPGAN is meticulously crafted for the enhancement and restoration of facial images, standing out for its specialized approach in leveraging a pre-trained facial GAN, specifically StyleGAN, as a generative facial prior. This unique methodology empowers GFPGAN to intricately capture and enhance facial details with exceptional effectiveness. By focusing on facial priors and integrating Channel-Split Spatial Feature Transform layers, GFPGAN tailors its processing specifically for facial images, promising superior results in facial enhancement tasks. This specialized architecture enables GFPGAN to comprehensively understand and enhance facial structures and details, offering a significant advancement in the realm of facial image enhancement technology.

Fig.4.Output of NoGAN

NoGAN presents a novel approach to image restoration, offering a blend of efficiency and realism. While ESRGAN excels in high-resolution upscaling and BSRGAN specializes in portrait restoration, NoGAN provides a unique methodology. By combining traditional pretraining with brief GAN training, NoGAN minimizes artifacts and glitches, catering to a wide range of restoration tasks. Its flexibility allows for customization based on specific requirements, making it a compelling option for scenarios where balancing realism and computational efficiency is crucial. NoGAN represents a significant advancement in restoration technology, promising superior results while addressing challenges encountered with traditional GAN-based models.

In the decision-making process for selecting the most appropriate model, our research suggests a nuanced approach based on specific application needs. ESRGAN proves to be the model of choice when prioritizing high-resolution upscaling, generating sharp and detailed outputs. BSRGAN shines in scenarios where portrait restoration is paramount, preserving natural features and textures. SwinIR emerges as a versatile solution, excelling across various restoration tasks but demanding more computational resources. GFPGAN is an ideal option for facial image enhancement due to its specialized architecture leveraging pre-trained facial GAN (StyleGAN) as a generative facial prior, ensuring superior results by capturing and enhancing intricate facial details effectively. The ultimate choice should be guided by a careful consideration of the intended application and the nuanced requirements of the restoration task at hand. Our research proposes the NoGAN approach as a promising alternative for model selection, particularly when considering the trade-offs between realism and computational efficiency. NoGAN offers a unique methodology that combines traditional pretraining techniques with brief GAN training sessions, prioritizing speed and reliability while still achieving realistic outputs. Unlike traditional GAN-based models, NoGAN significantly reduces the occurrence of artifacts and glitches, making it an attractive option for applications where minimizing such imperfections is crucial.

## VI.CONCLUSION

In summary, the suggested project on the restoration of criminal mugshot images through the use of preprocessing techniques and Generative Adversarial Networks (GANs) offers a possible solution to the drawbacks of current approaches. By systematically implementing cutting-edge deep learning algorithms, the initiative seeks to improve criminal mugshot quality and give law enforcement authorities more precise and trustworthy tools for identification and investigation.

Using GANs in conjunction with a Discriminator Network to evaluate image realism and a specialised Generator Network for image restoration provides an innovative approach. Preparing the dataset for best GAN performance involves a number of preprocessing procedures, such as scaling, noise reduction, Oldify effects, crack handling, black and white conversion, and scratches removal.

The project aims to address the drawbacks of conventional techniques, like the need for human preparation, general restoration techniques, and inadequate flexibility, by utilising deep learning. With its capacity to recognise intricate patterns and structures, the GAN architecture is anticipated to produce better outcomes when it comes to the restoration of criminal mugshot photos, which will ultimately lead to the development of more potent forensic technology.

*References*


[1] Isola, P., Zhu, J.-Y., Zhou, T., & Efros, A. A. (2017). "Image-to-Image Translation with Conditional Adversarial Networks." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

[2] Ledig, C., Theis, L., Huszar, F., Caballero, J., Cunningham, A., Acosta, A., Aitken, A., Tejani, A., Totz, J., Wang, Z., & Shi, W. (2017). Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

[3] M. Elad, B. Kawar, and G. Vaksman, "Image Denoising: The Deep Learning Revolution and Beyond -- A Survey Paper --," arXiv:2301.03362 [eess.IV], Jan. 2023.

[4] Feng, Z.-H., Kittler, J., Christmas, W., & Wu, X.-J. (2019). "Forensic Face Recognition Using Generative Adversarial Networks." In IEEE Transactions on Information Forensics and Security.

[5] Zhou Wang, A. C. Bovik, H. R. Sheikh and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," in IEEE Transactions on Image Processing, vol. 13, no. 4, pp. 600-612, April 2004.

[6] M. Lyons, S. Akamatsu, M. Kamachi and J. Gyoba, "Coding facial expressions with Gabor wavelets," Proceedings Third IEEE International Conference on Automatic Face and Gesture Recognition, Nara, Japan, 1998, pp. 200-205.

[7] Y. Zhang, Y. Tian, Y. Kong, B. Zhong and Y. Fu, "Residual Dense Network for Image Super-Resolution," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 2018, pp. 2472-2481, doi: 10.1109/CVPR.2018.00262.

[8] Karras, T., Aila, T., Laine, S., & Lehtinen, J. (2018). "Progressive Growing of GANs for Improved Quality, Stability, and Variation." In International Conference on Learning Representations (ICLR).