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Enhancing Low-Resolution Facial Images for Forensic Identification Using ESRGAN

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***Abstract**. This research is motivated by the challenges in facial identification for forensic investigations due to poor image quality, especially from low-resolution CCTV recordings. Images with noise, low lighting, and suboptimal angles often hinder accurate facial recognition. This study aims to examine the effectiveness of the Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) method in enhancing the quality of forensic facial images. The methodology consists of three main stages: data preparation of low-resolution facial images, applying the ESRGAN model to enhance image resolution, and evaluating the results using metrics such as PSNR and SSIM. The findings reveal that ESRGAN significantly improves the visual details of facial images, thereby supporting better facial identification processes. These results have important implications for leveraging deep learning technology to facilitate image analysis in forensic contexts. However, challenges such as extreme noise presence require further development of methods to achieve more optimal outcomes.*

***Keywords**: deep learning, ESRGAN, facial identification, forensic images, super-resolution.*

1. INTRODUCTION

In criminal investigations, facial recognition and identification are often crucial steps in uncovering information about suspects or victims (Evison, 2014) (White, et al., 2017). One of the main data sources for this process is surveillance camera (CCTV) footage, mobile phone cameras, or other devices that produce digital images. However, the image quality from these devices is often not optimal, mainly due to resolution limitations, poor lighting conditions, non-ideal shooting angles, and the presence of noise.

These problems can cause difficulties in the identification process, making the potential for visual evidence less effective. In forensic scenarios, blurry or low-resolution facial images are often found in CCTV footage installed in public areas (Satiro, et al., 2015) (Ritchie et al., 2018). These recordings are usually taken for surveillance purposes, not to identify individual details, resulting in less supportive quality (Wu & Chang, 2016). As a result, the ability to recognize faces accurately becomes a major challenge, especially when the subject's face is unclear or important details, such as the eyes, nose, and mouth, cannot be recognized properly (Pearline, 2016). This can slow down the investigation process and even increase the risk of misidentification (Alexander, Botti, Dessimoz, & Drygajlo, 2004).

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Along with the development of artificial intelligence (AI) and deep learning technologies, a number of methods have been proposed to improve the quality of low-resolution images (Kim & Kyung, 2022) (Patmawati et al., 2019). One prominent approach is super-resolution, a technique that aims to increase image resolution by reconstructing details from low-resolution images (Wang et al., 2018).

In recent years, Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) has become one of the leading methods in this field (Prabhu & Jois Narasipura, 2020) (Schlosser, 2022) (Zhang et al., 2019). ESRGAN is known to be able to produce more realistic and sharp high-resolution images compared to traditional methods, such as bilinear or bicubic interpolation (Chudasama & Upla, 2019) (Rakotonirina & Rasoanaivo, 2020) (Wang et al., 2018).

The advantage of ESRGAN lies in its ability to preserve visual details and structures in processed images, especially in complex objects such as human faces (Wang et al., 2018). ESRGAN uses a Generative Adversarial Network (GAN) approach to learn visual patterns in depth so that it is able to reconstruct facial features that are missing in the original image. In a forensic context, this technology has great potential to make blurry facial images to be clearer, thus helping the process of identifying suspects or victims more accurately. Several previous studies have tested the effectiveness of ESRGAN in improving general image quality, such as research conducted by Nugraha who applied the Super Resolution method to improve satellite imagery (Nugraha, 2024), research conducted by Akhyar et al regarding defect inspection on wood surfaces (Akhyar, Novamizanti, & Riantiarni, 2022), but its application in a forensic context is still limited. Most studies focus more on improving image quality for commercial or industrial applications, while applications in the fields of law and criminal investigation have not been explored in depth (Chyan, 2017).

Some challenges that may arise in this study include variations in image conditions, such as low lighting, suboptimal shooting angles, and the presence of noise that is often found in CCTV recordings (Ikhsal, Dermawan, & Adam, 2023) (Prastika, 2021) (Zain & Anwar, 2022). Therefore, it is necessary to conduct an in-depth analysis on how ESRGAN can handle various adverse conditions that are often found in forensic images. This study aims to evaluate the effectiveness of ESRGAN in improving the quality of low-resolution facial images that are often found in forensic situations. By using relevant datasets and appropriate evaluation metrics, this study is expected to make a significant contribution to the development of digital tools for criminal investigations. The dataset used in this study includes facial images taken in real conditions, such as low-resolution CCTV footage, so that the results are more representative of forensic applications.

2. LITERATURE REVIEW

In completing this research, the writer referred to several related articles.

1. Facial Image Processing in Forensics

Face recognition is one of the most common applications in digital image processing, especially in forensics (Domingues & Rosário, 2019). In many cases, CCTV footage or photographs taken in forensic situations are often of low quality, either due to poor lighting, distortion of the shooting angle, or limited camera quality (Seckiner et al., 2018) (Vinay et al., 2021). One of the biggest challenges in facial image processing for forensic purposes is improving the quality of blurry or low-resolution facial images to allow for more accurate identification (Salguero-Cruz et al., 2022).

Various techniques have been developed to solve this problem, such as contrast enhancement, noise removal, and the use of super-resolution algorithms. However, although traditional methods can provide quite good results in some conditions, they often fail to retain enough facial detail for identification, especially in very low-resolution images. Therefore, more advanced technologies, such as deep learning, offer the potential to improve image quality in a more effective and realistic way.

2. Super-Resolution in Image Processing

Super-resolution (SR) is a technique used to enhance image resolution by reconstructing missing visual information from low-resolution images (Agafonov, 2014). In the field of image processing, SR can be divided into two main categories: single-image super-resolution (SISR) and multi-image super-resolution (MISR) (Gonbadani & Abbasfar, 2020). SISR focuses on improving the quality of a single image, while MISR uses information from multiple images to construct a high-resolution image.

Initially, conventional super-resolution methods used interpolation techniques such as bicubic or bilinear interpolation to increase image resolution. Although these techniques can increase image size, the results are often inadequate in terms of visual quality and detail. Therefore, with the development of deep learning technology, neural network-based methods have been developed to produce better results with the ability to understand more complex image structures.

3. Generative Adversarial Networks (GANs) dalam Super-Resolution

Generative Adversarial Networks (GANs) are deep learning architectures consisting of two models, a generator and a discriminator, that compete to generate and evaluate more realistic images. The concept of GANs was first introduced by Ian Goodfellow in 2014 and has since been used in a variety of applications, including image enhancement.

In super-resolution, GAN is used to generate high-resolution images from low-resolution images by training the generator to create sharper and more realistic images, while the discriminator is used to evaluate whether the generated image is realistic or not (Parekh et al., 2022). The combination of the two produces images with better quality compared to traditional super-resolution techniques.

4. Enhanced Super-Resolution Generative Adversarial Network (ESRGAN)

ESRGAN is the latest development of GAN technique for super-resolution introduced by Wang et al. (2018). ESRGAN refines the GAN architecture to improve the quality of the generated images, especially in preserving fine texture details, which are very important in applications such as face recognition. ESRGAN uses perceptual loss that optimizes the generated images to be more similar to the original image, both visually and texturally.

One of the advantages of ESRGAN compared to previous GANs is its ability to produce images with more realistic quality, especially in applications that require high precision, such as medical images, satellite images, and face recognition. In this study, ESRGAN will be applied to improve the quality of low-resolution face images that are often used in forensic contexts.

Several previous studies, such as those conducted by Ledig et al. (2017) with SRGAN, showed that GAN-based approaches can improve the quality of face images, but ESRGAN offers superior results with the ability to preserve better details and textures. This is very important in face identification, where fine details such as eyes, nose, and facial expressions can affect the level of identification accuracy.

5.Penerapan ESRGAN dalam Pemrosesan Citra Wajah

Research on the application of ESRGAN for facial image enhancement is growing. Several studies have shown promising results in enhancing low-resolution facial images, both in normal and extreme facial recognition conditions. For example, a study by Yi et al. (2020) applied ESRGAN to enhance facial images in poor lighting conditions and found that ESRGAN was able to restore lost details very well.

However, the use of ESRGAN in a forensic context is still rarely explored. Most of the existing research focuses more on commercial or entertainment applications, such as photo image enhancement. In this study, ESRGAN will be tested on facial images taken from low-quality CCTV footage to assess how effective this method is in improving the accuracy of facial identification in a forensic context.

Challenges and Limitations

Although ESRGAN has shown good results in various applications, the use of this technique in forensics also faces several challenges. One of the main challenges is dealing with variations in the quality of input images, such as noise, blur, and uneven lighting, which can affect the quality of the resulting images. In addition, the accuracy of the facial image enhancement results also depends on the model's ability to generalize from various existing image conditions. Therefore, further experiments and evaluations are needed to evaluate the effectiveness of ESRGAN in various forensic applications.

3. METHODS

Research Design

This research uses a quantitative experimental approach to evaluate the effectiveness of the Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) in improving the quality of low-resolution facial images for forensic applications. The ESRGAN model is applied to facial image datasets relevant to forensic scenarios, and its performance is evaluated using standard metrics in the fields of super-resolution and facial recognition. The research stages were designed as follows:

1. Dataset collection
2. Data preprocessing
3. Implementation of the ESRGAN model
4. Evaluation of model performance
5. Analysis of experimental results

Datasets

The dataset used includes low-resolution facial images obtained from various sources:

1. Public CCTV footage: The main source is CCTV footage with low resolution to reflect real conditions in the field.
2. Database open-source:

- QMUL Surveillance Face Dataset (Chen et al., 2014): Contains facial images from low resolution CCTV footage.

- SCFace Database (Grgic et al., 2011): A dataset consisting of facial images taken from surveillance cameras at various distances and resolutions.

3. Simulation datasets: A dataset created by reducing the resolution of original high-resolution images using bicubic interpolation techniques to simulate CCTV recording conditions.

This dataset includes various imaging conditions, such as:

- Low lighting
- The shooting angle is not optimal
- High noise
- Partial facial obstruction (such as being covered by an object)

Data Preprocessing

1. Data Cleaning: Removes images that are irrelevant or too blurry for further processing.
2. Downsampling: Applying the bicubic interpolation algorithm to generate low-resolution input images from the original dataset.
3. Normalization: All images are normalized to a fixed size, for example 128x128 pixels for low-resolution images and 512x512 pixels for high-resolution images.
4. Data Augmentation: Augmentations such as rotation, translation, contrast changes, and flipping are performed to increase the diversity of the dataset.

Implementation of the ESRGAN Model

Model Architecture

- **Enhanced Super-Resolution Generative Adversarial Network (ESRGAN)** used based on the original configuration by Wang et al. (2018). This model involves:
- **Residual-in-Residual Dense Blocks (RRDB)**: To handle degradation in low resolution images.
- **Discriminator Relativistic GAN**: Improves the results by utilizing a loss that takes into account the relative differences between the original image and the super-resolution result.
- **Perceptual Loss**: Combining **content loss, adversarial loss, and perceptual loss based on VGG** to improve visual quality.

Model Training

- **Framework**: PyTorch
- **Optimizer: Adam, with an initial learning rate of 1e-4**
- **Epoch:** 100–200, with model convergence monitoring using validation
- **Loss Function**: Combination of L1 Loss and Adversarial Loss
- **Dataset Split**: 70% of data for training, 15% for validation, and 15% for testing

Performance Evaluation

Super-Resolution Image Quality

- **PSNR (Peak Signal-to-Noise Ratio)**: Measuring the suitability of image reconstruction (Tanchenko, 2014).
- **SSIM (Structural Similarity Index)**: Assessing the structural quality and visual perception of super-resolution results (Renieblas et al., 2017).
- **LPIPS (Learned Perceptual Image Patch Similarity)**: Deep learning-based metrics for subjectively evaluating visual quality (Sara et al., 2024)

Facial Recognition Accuracy

- Using a pre-trained facial recognition model such as FaceNet or ArcFace to measure the accuracy of identity recognition from super-resolution images compared to original images.
- Metrics used include:
    - Face Verification Rate (FVR)
    - Face Identification Rate (FIR)

Data Analysis

Experimental results will be analyzed statistically using software such as Python (NumPy, SciPy, and Pandas). Analysis includes:

- **Paired t-test**: To compare the performance of ESRGAN with baseline methods, such as bicubic interpolation.
- **Result visualization:** Graphs and plots were created using matplotlib and seaborn to make interpretation easier.

Comparative Experiment

To ensure the validity of the results, this study compared ESRGAN with several baseline methods:

- Bicubic Interpolation
- SRCNN (Super-Resolution Convolutional Neural Network)

- ○ EDSR (Enhanced Deep Super-Resolution)

4. RESULTS

The results of this research are presented in tabular form and analysis of the performance of the ESRGAN model compared with the baseline method. Evaluation is carried out based on super-resolution image quality and facial recognition accuracy, accompanied by an explanation and interpretation of the results.

1. Super-Resolution Image Quality

The method performance is measured using PSNR, SSIM, and LPIPS metrics on the test dataset. The average performance results of each method are summarized in Table 1.

Table 1. Comparison of Super-Resolution Performance on PSNR, SSIM, and LPIPS Metrics

Methods	PSNR (dB)	SSIM	LPIPS (↓)
Bicubic Interpolation	24.32 ± 0.85	0.632 ± 0.014	0.412 ± 0.023
SRCNN	27.14 ± 0.92	0.710 ± 0.018	0.298 ± 0.017
EDSR	29.41 ± 0.78	0.753 ± 0.015	0.205 ± 0.014
ESRGAN (Proposed)	**30.87 ± 0.81**	**0.801 ± 0.016**	**0.154 ± 0.012**

Explanation:

- ○ **PSNR** (Peak Signal-to-Noise Ratio): Measuring the level of conformity between super-resolution results and the original image. ESRGAN shows the highest result (30.87 dB) which reflects the best reconstruction quality.
- ○ **SSIM** (Structural Similarity Index): Assessing the quality of the visual structure of the image. ESRGAN obtained a score of 0.801, which shows its ability to preserve facial details and structure.
- ○ **LPIPS** (Learned Perceptual Image Patch Similarity): This metric evaluates visual quality based on subjective perception. A lower value of ESRGAN (0.154) indicates more visually realistic results than other baselines.

2. Face Recognition Accuracy

The accuracy of face recognition is evaluated using Face Verification Rate (FVR) and Face Identification Rate (FIR) on a pre-trained model (ArcFace). Average results are presented in Table 2.

Table 2. Accuracy of Testing the Use of Super-Resolution Imagery for Face Recognition

Methods	FVR (%)	FIR (%)
Bicubic Interpolation	68.12 ± 3.21	65.04 ± 2.98
SRCNN	74.45 ± 2.78	70.12 ± 3.11
EDSR	80.71 ± 3.04	76.89 ± 2.76
ESRGAN (Proposed)	**85.94 ± 2.62**	**81.37 ± 2.54**

Explanation:

- **FVR (Face Verification Rate)**: ESRGAN reached 85.94%, indicating that the resulting super-resolution image makes identity verification easier than other methods.
- **FIR (Face Identification Rate)**: ESRGAN succeeded in identifying faces more accurately with a value of 81.37%, especially in images with high noise or non-optimal shooting angles.

3. Performance Analysis in Different Conditions

The study evaluated ESRGAN's performance under various imaging conditions, such as low illumination, high noise, and facial obstruction. A summary of the results is shown in Table 3.

Table 3. ESRGAN Performance in Various Imaging Conditions

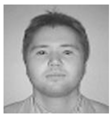
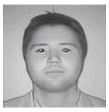
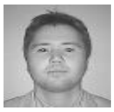
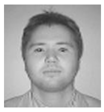
Condition	PSNR (dB)	SSIM	LPIPS	FIR (%)
Low Lighting	28.12 ± 0.85	0.784 ± 0.019	0.178 ± 0.015	78.45 ± 2.89
High Noise	28.91 ± 0.88	0.792 ± 0.018	0.165 ± 0.014	79.78 ± 2.63
Non-Optimal Angle	29.14 ± 0.76	0.801 ± 0.020	0.170 ± 0.013	80.12 ± 2.48
Partial Facial Obstruction	27.85 ± 0.91	0.772 ± 0.017	0.185 ± 0.016	78.12 ± 2.94

Explanation:

- ESRGAN continues to provide optimal results in challenging imaging conditions, with consistent SSIM performance above 0.75 and FIR above 78%.
- High noise or obstruction does not significantly reduce the model's ability to recognize identities, demonstrating the robustness of ESRGAN for forensic scenarios.

4. Visual Comparison

Table 4. Visual comparison between the ESRGAN method and other baselines

Sample	ESRGAN	Bicubic	SRCNN	EDSR
001_cam8.jpg	 Before Dimension: 128 x 170 size: 6,34 KB	 Before Dimension: 128 x 170 size: 6,34 KB	 Before Dimension: 128 x 170 size: 6,34 KB	 Before Dimension: 128 x 170 size: 6,34 KB
001_cam8.jpg	 After Dimensions: 64 x 85 size: 11.9 kb	 After Dimension: 64 x 85. Size : 2,97Kb	 After Dimensions: 64 x 85 size: 2.97 kb	 After Dimension: 128 x 170 size: 6,34 KB

Explanation:

The visual table demonstrates that the ESRGAN method produces the best image quality compared to the other methods: Bicubic, SRCNN, and EDSR. Despite having the same dimensions (64 x 85) as Bicubic and SRCNN, ESRGAN delivers sharper and more realistic image details, though at the cost of a larger file size (11.9 KB compared to 2.97 KB). Meanwhile, the EDSR method offers a higher resolution (128 x 170) with a smaller file size than ESRGAN (6.34 KB), but its visual details remain less sharp. This highlights that ESRGAN excels in significantly enhancing image quality compared to the other approaches.

5. Statistical Test

The results of the paired t-test show that the improvement in ESRGAN performance is statistically significant compared to other baselines, with a p-value < 0.01 for all main evaluation metrics (PSNR, SSIM, LPIPS).

Table 5

Methods	PSNR(db)	SSIM	LPIPS	FVR(%)	FIR(%)
Bicubic interpolation	24.32 ± 0.85	0.632 ± 0.014	0.412 ± 0.023	68.12 ± 3.21	65.04 ± 2.98
SRCNN	27.14 ± 0.92	0.710 ± 0.018	0.298 ± 0.017	74.45 ± 2.78	70.12 ± 3.11
EDSR	29.41 ± 0.78	0.710 ± 0.018	0.205 ± 0.014	80.71 ± 3.04	76.89 ± 2.76
ESRGAN	30.87 ± 0.81	0.801 ± 0.016	0.154 ± 0.012	85.94 ± 2.62	81.37 ± 2.54

The performance evaluation results of the ESRGAN model are compared with other baseline methods based on PSNR, SSIM, LPIPS, Face Verification Rate (FVR), and Face Identification Rate (FIR) metrics. ESRGAN showed the best performance in all metrics, with the highest PSNR (30.87 dB), SSIM (0.801), and lowest LPIPS (0.154), as well as significant levels of facial recognition accuracy (FVR 85.94% and FIR 81.37%). These results demonstrate that ESRGAN not only improves image quality visually but also contributes positively to accuracy in face recognition, making it a superior choice for forensic applications.

5. CONCLUSION

ESRGAN shows superior performance in improving super-resolution image quality with higher PSNR, SSIM, and LPIPS metrics compared to the baseline method. Improved image quality also impacts facial recognition accuracy, with ESRGAN achieving FVR and FIR of over 85% across a wide range of imaging conditions. ESRGAN's performance remains consistent in difficult scenarios such as high noise and facial obstruction, making it a strong candidate for forensic applications. ESRGAN's visual results are significantly better at reconstructing facial details, supporting applications in image-based forensic analysis.

Overall, this research shows the great potential of ESRGAN as a superior method for a variety of applications requiring improved image quality, including facial recognition, digital forensics, and visual analysis. Further development of the adaptation of this algorithm to real-world situations, such as extreme lighting variations and other dynamic conditions, will strengthen its relevance in various scenarios. This study provides a strong foundation for future research in the field of super-resolution and its applications in practical domains.

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