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Noise-resilient face recognition system: A review of denoising approaches and their impact on accuracy

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Abstract

Noise interference and inconsistent image quality pose growing issues for facial recognition systems particularly in urban surveillance settings. While traditional denoising techniques, such as wavelet-based transforms and other classical methods are good at retaining texture, they are not very effective when dealing with complicated noise patterns and high computing demands. Consequently, low-power or embedded applications have found success with lightweight improvements like Local Binary Patterns (LBP). Nonetheless, their limited capacity to interpret high-resolution and color pictures limits their wider use. The advantages and disadvantages of these traditional and contemporary methods are critically examined in this paper, with an emphasis on deep learning-based models like Stacked Denoising Autoencoders (SDAE). Although these models are prone to overfitting and necessitate careful parameter adjustment, they have demonstrated impressive effectiveness in learning noise-robust representations. The study also investigates the possibility of combining stacked autoencoders and Histogram of Oriented Gradients (HoG) as a hybrid approach to get over current bottlenecks. Based on this investigation, a robust denoising framework can be achieved by combining the denoising power of SDAEs with the edge-preserving capabilities of HoG for enhanced feature extraction under structured and mixed noise conditions. This integration is positioned as a future-ready solution for building scalable, real-time, and noise-resilient facial recognition pipelines.

Nomenclature and units

YOLO	You Only Look Once
MTCNN	Multi-task Cascaded Convolutional Networks
LBP	Local Binary Patterns
CNN	Convolutional Neural Networks
DAE	Denoising Autoencoders
AE	Autoencoder
BM3D	Block-Matching and 3D Filtering
NLM	Non-local Means
TV	Total Variation Denoising
HoG	Histogram of Oriented Gradients
PSNR	Peak Signal-to-Noise Ratio
SSIM	Structural Similarity Index.
SDAE	Stacked Denoising Autoencoders

1.0 Introduction

As the world population grow day by day, crimes and insecurity have increased rapidly in urban areas [1]. In order to cube the crimes and tightening security, since 1960's several face recognition systems have been developed from traditional feature extraction methods to advanced deep learning-based models. These systems enhance security where by real time surveillance and prompt identification of individuals, contributes to faster case resolution and crime prevention and also efficiency identification [2]. However, their effectiveness depends on various factors, such as noise management, lighting conditions, image blur and fairness [3]. Facial recognition technology relies on the uniqueness of a person's face, and this approach takes a step further by considering the individual's history of criminal activities [4]. A typical face recognition system consists of the following key stages, Face detection, pre-processing, Feature extraction and Face detection [5]. The contributions of the individual steps are highlighted as follows:

a. Face Detection**:** The initial step is to identify and locate faces in a stream of images or videos. Usually, methods like the Haar Cascade classifier or HOG (Histogram of Oriented Gradients) are used to do this. To detect faces more precisely in real time, modern systems use deep learning-based models like YOLO (You Only Look Once) and MTCNN (Multi-task Cascaded Convolutional Networks) [3].
b. Pre-processing: Pre-processing ensures consistent face quality by correcting variations such as: Lighting normalization where brightness or shadows is adjusted to improve uniformity, Image alignment where face is aligned based on key landmarks (e.g., eyes, nose) to reduce angle variation, and noise reduction where filters are employed to remove unwanted noise and enhance feature extraction accuracy [6].
c. Feature Extraction: This stage converts the raw face image into a feature vector that captures essential facial attributes. Techniques include: Handcrafted features: where textures and facial structures are analysed by algorithms such as Gabor filters or Local Binary Patterns (LBP) and deep learning models where Convolutional Neural Networks (CNNs) far outperform conventional techniques in complicated circumstances by automatically extracting high-dimensional characteristics [7].
d. **Face Matching or Recognition:** To identify or confirm a person's identity, the retrieved attributes are compared with stored data [8]. Some matching techniques are but not limited to [9].:
   i. Euclidean distance: Determines the separation between feature vectors to assess similarity.
   ii. Cosine similarity: Evaluates how different vectors are angularly.
   iii. Classification models: Neural networks are used by certain systems to directly classify users into known identities.

The diagram in Figure 1 depicts the typical face detection or recognition process.

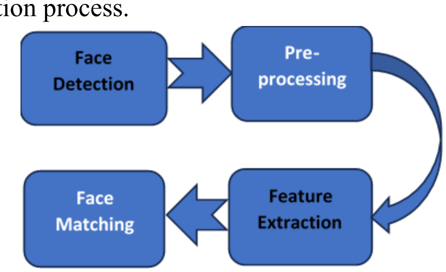

Figure 1: Typical Face Recognition Process

However, the effectives of the recognition process presented in Figure 1, is highly dependent on the noise present in the image. These noises are inherent in the image, making facial recognition process difficult. Thus, leading to inaccuracy of the face recognition systems. As such, this study presents a review of different denoising approaches and their impact on accuracy with a view to deploying noise-resilient face recognition system in real-life applications**.** The contributions of the review are as follows:

a. Specific requirements for denoising algorithms that are tailored to deploying noise resilient face recognition systems are determined and presented with a view to providing real-life implementation on urban streets.
b. The review identified strategies that can be employed to enhance the noise reduction model.
c. The review provided practical solutions for street surveillance systems, contributing to safer urban environments and advancing academic knowledge in image processing, machine learning, and surveillance technology.

The remaining part of the paper is organized as follows: Section II details the basic concept and algorithm types. Section III presents the pertinent reviews for this study, while Section IV presents the discussions of the findings. Finally, in Section V, the authors summarize the conclusions and recommendations for future work.

2.0 Basic Concepts and Algorithms Types

Noise can be defined as any unwanted features that makes it hard to identify someone or something in an image [6]. The kinds and intensities of these noises differ. Usually, an image has noise that needs to be filtered out. Images can be impacted by a variety of noise sources. These noise kinds include, but are not restricted to: Salt & pepper noise, blur, speckle noise and gaussian noise[10]. Speckle noise happens when pixels are multiplied by a random factor due to random multiplicative noise. Blur occurs as a result of the image's haziness or unsharp Ness. Typically, due to camera motion, or other elements. Speckle noise, which includes dark current, read noise, and thermal noise, is typically brought on by the camera sensor [11], Gaussian Noise is Statistical noise that has a probability density function (PDF) equivalent to the normal distribution. The diagram in Figure 2 depicts the different types of noise

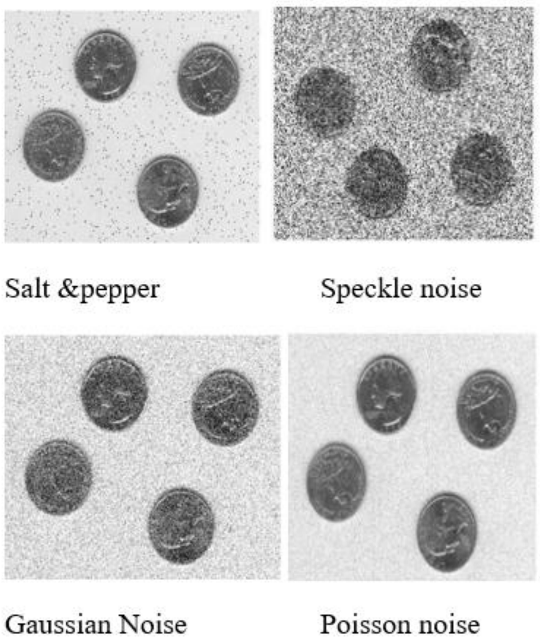

Figure 2: The Common types of Noise that affects Facial Recognition Systems [11]

Noise in mages is a critical problem in face recognition systems mostly in security matters that needs rectified by denoising algorithms and models [12]. Advanced models typically incorporate techniques like Gaussian, uniform, or salt-and-pepper noise handling, which are frequent in real-world data [13]. These types of noise affect both the pixel distribution and clarity of images, requiring specific pre-processing steps for mitigation. In order to extract reliable characteristics, face recognition systems are increasingly using deep learning models, particularly Convolutional Neural Networks (CNNs). CNNs may be susceptible to noisy data, though, which is why noise-resistant models are being incorporated for improved performance [14]. Some known algorithms that are employed to remove noise in facial images are:

i. Wavelet-Based Methods**:** Wavelet-based denoising methods have been widely used in image processing. These methods leverage the mathematical framework of wavelet transforms to decompose images into different frequency components [15]. By thresholding the coefficients in the wavelet domain, these methods effectively suppress noise while preserving important image features [16]. However, one of the limitations of wavelet-based denoising is the challenge in selecting appropriate thresholds, and their performance may degrade under complex noise patterns.

ii. Block-Matching and 3D Filtering (BM3D)**:** BM3D is a popular denoising algorithm that exploits both 2D and 3D collaborative filtering. It operates by grouping similar blocks from a 3D data array and applying collaborative filtering within these groups [17]. BM3D has demonstrated impressive denoising performance, especially in the presence of additive white Gaussian noise. However, its computational complexity can be high, making it less suitable for real-time applications in surveillance systems.

iii. Denoising Autoencoders**:** Denoising autoencoders are a type of artificial neural network trained to reconstruct clean images from noisy inputs. These models learn a mapping from noisy to clean data, effectively denoising the images in the process. By doing this, the DAE can identify important characteristics in the incoming data while ignoring noise and unimportant details [18]. The DAE loss function is expressed as follows:

$$L_{DAE}(X, X^{'}) = \min\left(\| X - X^{'} \|_F^2 \right) \qquad (1)$$

where X represents the clean input data, and X̂′ denotes the noisy input data. While denoising autoencoders have shown success in various applications, training deep neural networks needs extensive computational resources, and their performance might be sensitive to the amount and type of noise in the training data.

iv. Non-local Means (NLM): NLM is a non-local denoising algorithm that operates by averaging the pixel values of similar patches in the image. This approach exploits redundancies in the image to distinguish between noise and actual features. NLM is known for its ability to handle different types of noise and is relatively computationally efficient. However, its performance can degrade in the presence of strong noise [19].

v. Total Variation Denoising**:** Total Variation (TV) denoising is a regularization method that aims to preserve edges while reducing noise in images [20]. It achieves this by minimizing the total variation of the image, effectively smoothing regions with little variation while preserving important features. TV denoising is computationally efficient and suitable for real-time applications [21], but it may over smooth textured regions.

vi. Low-Complexity Algorithms: Recognizing the limitations of existing denoising algorithms, recent studies have emphasized the development of low-complexity models. These algorithms, such as Local Binary Pattern (LBP) with Stacked Autoencoder (AE), prioritize efficiency without compromising denoising effectiveness. LBP captures local patterns, and Stacked AE further reduces noise impact, making them promising candidates for real-time applications in street surveillance.

vii. Local Binary Pattern: This is a texture descriptor widely used in image analysis and computer vision [22]. It operates by assigning a binary code to each pixel in an image based on the relative intensity of its neighbours [23]. A low binary pattern (LBP) is a simple yet powerful feature descriptor for facial recognition. It encodes the local texture information of an image by comparing the intensity of each pixel with its neighbours and assigning a binary code. The LBP can be computed efficiently and is robust to illumination changes and noise [24]. The mathematical background of LBP is based on the concept of uniform patterns, which are binary patterns that have at most two bitwise transitions from 0 to 1 or vice versa. For example, 00000000, 01110000, and 01011011 are uniform patterns, but 01010101 is not. Uniform patterns account for about 90% of all possible patterns in natural images, and thus reduce the dimensionality and complexity of the feature space. Some applications of LBP include face detection, face recognition, facial expression analysis, gender classification, and age estimation [25].

The LBP operator is defined as follows:

$$LBP_{P,R}(x_c) = \sum_{p=0}^{P-1} s(g_p - g_c) \times 2^p \qquad (2)$$

Where:

P is the number of neighbours,
R is the radius
x_c represents the central pixel,
g_p is the intensity of the p-th neighbours?
g_c is the intensity of the central pixel?
$s(z)$ is a step function defined as $s(z) = \begin{cases} 1 & if\ z \geq 0 \\ 0 & otherwise \end{cases}$

The binary code generated by LBP captures local patterns in the image, providing a robust representation of texture. When applied to facial recognition, LBP-based denoising becomes crucial for maintaining the integrity of facial features, especially in scenarios with varying environmental noise. The LBP process model is shown in Figure 3

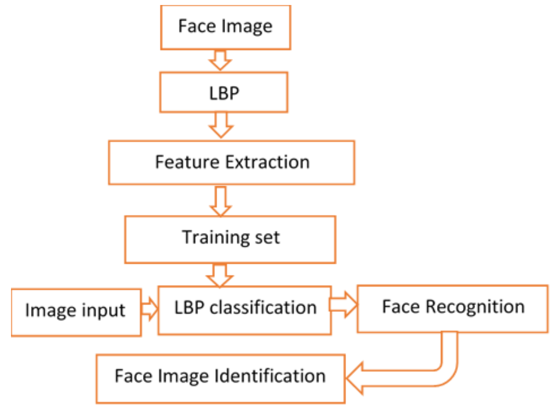

Figure 3: Typical LBP Process [25]

viii. Histogram of Oriented Gradients (HOG) is a feature descriptor that is frequently employed in facial recognition and computer vision because of its capacity to capture texture and edge information. The gradient orientation in each of the tiny cells that make up an image is calculated by HOG. After that, it creates a histogram of these orientations to depict the image's structure and form. HOG has demonstrated success in various applications, including face recognition. Studies by [26] have implemented HOG for facial recognition in video sequence, demonstrating its effectiveness in preserving essential features while removing noise.

The performance metric used to evaluate these algorithms are:

1. PSNR defined by equation (3)

$$\text{PSNR} = 10\ .\ log_{10}(\frac{MAX^2}{MSE}) \qquad (3)$$

Where; MAX is the maximum possible pixel value (e.g., 255 for an 8-bit image). MSE (Mean Squared Error) is calculated as the average of the squared differences between corresponding pixels of the original and denoised images.

2. SSIM defined by equation (4)

$$SSIM(\text{x}, \text{y}) = \frac{(2\cdot\mu_x\cdot\mu_y + c_1)(2\cdot\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)\cdot(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (4)$$

Where; μ_x and μ_y are the means of the original and denoised images. σ_x^2 and σ_y^2 are the variances, $\sigma_{xy}$is the covariance. c_1 and c_2 are constants to avoid instability when the denominator is close to zero.

3.0 Pertinent Reviews

This subsection presents the review of pertinent works. The papers are selected randomly in no superior order. However, papers selected randomly are those that have employed one or in combination of the existing algorithms to remove noise from facial images.

[9] used machine learning techniques to create a face recognition framework. General-purpose filters might not be enough for reliable recognition in a variety of environmental situations, according to the study, which emphasized the necessity of adaptively tweaking pre-filter types. In a similar vein, [15] investigated a wavelet-based feature improvement method for facial recognition in a different study. Despite demonstrating encouraging outcomes in controlled environments, the approach's effectiveness significantly deteriorated when exposed to complex or mixed noise sources, suggesting limits in real-world deployment scenarios.

[27] conducted comparative evaluations of denoising algorithms to enhance facial recognition outcomes. In a notable study, researchers compared the performance of traditional denoising methods such as Gaussian filters and median filters with advanced deep learning-based approaches. The evaluation considered metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSI). The results indicated that deep learning-based algorithms, particularly convolutional neural network (CNN)-based denoising, outperformed traditional methods in preserving facial features and enhancing recognition accuracy. The study recommended the adoption of deep learning models for improved denoising in facial recognition systems, emphasizing their efficacy in handling complex noise patterns. In a more data-driven approach, [28] introduced a data-driven denoising technique leveraging generative adversarial networks (GANs). The model showcased unprecedented performance in preserving fine details while eliminating noise. A hybrid model that combines statistical methods with machine learning techniques to denoise facial images captured in real-world urban scenarios was presented by the work of [29]. The study underscored the importance of tailoring denoising algorithms to the complexities of urban surveillance environments. [30], developed system for automatic image denoising whereby different deep learning techniques were evaluated in terms of their impact on the quality of object detection/recognition to denoise images that were affected by a variety of adverse weather conditions that made it hard to detect objects correctly. A thorough analysis contrasting state-of-the-art machine learning-based algorithms with conventional denoising techniques was carried out by [31]. The study valuated robustness to various noise kinds, accuracy, and computational efficiency and came to the conclusion that contemporary algorithms perform noticeably better than older ones, especially in intricate urban surveillance scenarios. [32] concurrently examined the function of Local Binary Patterns (LBP) in facial recognition, emphasizing how well it works as a straightforward yet potent technique for feature extraction and texture description. Their investigation verified that LBP and its variations are widely used in everyday biometric and authentication systems because of their robust performance and ease of computation. A new hybrid denoising technique that combines fuzzy logic and deep learning was presented by [33]. Although the model showed remarkable denoising performance in urban surveillance settings, the study found no discussion of how it handled particular difficulties in denoising street images in the real world, indicating the need for more testing in real-world applications. [34] investigated different denoising algorithms in order to determine how they affected the accuracy of facial recognition. Although the study's conclusions were perceptive, there was no discussion of how these algorithms might be used in dynamic urban monitoring settings. [35] provided an assessment of denoising methods in conjunction with biometric image categorization, building on deep learning methodologies. The study demonstrated how deep learning models can enhance image quality, but it did not thoroughly analyze the various noise issues that are frequently present in street-level photography.

Table I summarizes all the results discussed in this section.

Table 1 The summary of the reviewed works.

S/N	Author, Year, Title	Work Done	Observed Limitation
1	[9]	Face Recognition Using Machine Learning	Needs tuning of pre-filter types per noise type
2	[15]	Wavelet-Based Feature Enhancement for Face Recognition	Performance drops under complex or mixed noise
3	[27]	Comparative evaluations of denoising algorithms	Doesn't specifically address challenges in urban surveillance scenarios.
4	[28]	data-driven denoising technique leveraging generative adversarial networks (GANs)	Limited discussion on the algorithm's applicability to street image denoising challenges
5	[29]	hybrid model for handling diverse noise sources in real-world urban scenarios.	Limited discussion on the model's performance under specific street image denoising challenges
6	[30]	Image Denoising for Video Surveillance Cameras Based on Deep Learning Techniques	Concentrated on objects lacking in face recognition
7	[31]	Comprehensive comparison between traditional denoising techniques and	Limited exploration of denoising algorithms under specific urban challenges such as

		machine learning-based methods.	occlusions, low lighting, and poor image quality.
8	[32]	Local Binary Patterns and Its Application to Facial Analysis	Exploration of LBP only in denoising street images is susceptible to noise
9	[33]	Proposed a novel hybrid model incorporating elements of deep learning and fuzzy logic for remarkable denoising capabilities in urban surveillance environments.	Limited discussion on the model's performance in handling specific street image denoising challenges for real life deployment.
10	[34]	Comparative evaluations of denoising algorithms, analyzing their effectiveness in improving facial recognition outcomes.	Limited discussion on the applicability of evaluated algorithms to real-world urban surveillance conditions
11	[35]	An evaluation of denoising techniques and classification of biometric images based on deep learning.	Lack of a broader evaluation encompassing various denoising challenges encountered in street images

4.0 Discussions

The findings are synthesized and discussed across major algorithmic categories for determining the specific requirement tailored to real life deployment of a noise-resilient face recognition system.

The review found that classical methods like BM3D and Wavelet transforms remain competitive due to their strong texture-preserving capabilities and low model complexity. BM3D demonstrated improved accuracy and was particularly effective on grayscale facial images. Wavelet techniques-maintained edge features with good accuracy. However, both methods showed performance degradation in the presence of structured or mixed noise types and lacked adaptability for real-time or resource-constrained deployment due to computational overhead.

Local Binary Pattern-based enhancements were found to offer a 28% improvement over standard LBP methods with minimal computational demand, making them suitable for embedded or low-power systems, though they underperform on color or high-resolution inputs as compare the HoG.

Also, Autoencoder-based models, especially Stacked Denoising Autoencoders, provided a significant leap in flexibility and performance, reaching up to 90% accuracy by learning noise-robust representations. Noise2Noise innovatively eliminated the need for clean target images, achieving 93% accuracy on the LFW dataset. These models, however, are susceptible to overfitting, sensitive to noise distributions, and require careful tuning of hyperparameters and architecture depth. Moreover, generative models like Cycle GAN and cGAN-TOP allowed for structure-preserving denoising even in unpaired or 3D point cloud data, with improvements of up to 14.81% in recognition accuracy.

4.1 Recommendations and Future Directions

As observed, traditional methods like BM3D, Wavelet transforms, and local binary pattern variants remain highly relevant for resource-constrained environments, offering competitive performance with minimal computational overhead. For scenarios involving unpaired data or limited ground-truth availability, unsupervised learning approaches such as Cycle GAN and Noise2Noise provide flexible alternatives. However, for low power systems and resource constrained deployment, the stack autoencoder is most suitable as observed.

Therefore, as a future direction and real-life deployment of facial recognition un urban streets, the authors will consider the integration of the stacked autoencoder and HoG. Combining the abstract, noise-invariant representations from Autoencoders with the spatial fidelity and edge-preserving characteristics of HoG can lead to a balanced and robust feature pipeline for real life deployment

5.0 Conclusions

This study presents a tailored review of denoising techniques applied to facial recognition systems for real life deployment. This review was done within the context of real-world urban surveillance. The results highlight the advantages and disadvantages of traditional techniques like Wavelet transforms, which work well for preserving textures but suffer from structured or mixed noise and real-time deployment limits. Similarly, LBP-based improvements perform worse in high-resolution and color imaging settings even though they are computationally efficient.

Superior noise robustness and adaptable learning capabilities are provided by deep learning-based models, particularly Stacked Denoising Autoencoders. Nevertheless, they are sensitive to architectural adjustment and need a large amount of training data. In light of these findings, the integration of Stacked Autoencoders and Histogram of Oriented Gradients (HoG) is proposed as light weight deployment of noise resilient facial recognition system.

A future direction for creating reliable, real-time face recognition systems is the combination of stacked autoencoders and histogram of oriented gradients (HoG). The goal of this hybrid framework is to integrate the edge-preserving, spatially sensitive feature extraction of HoG with the noise reduction powers of autoencoders. The methodology will bridge the gap between research innovation and practical implementation in real-world urban surveillance situations by improving adaptability, reliability, and computational efficiency while addressing the shortcomings of current methods in handling structured and mixed noise.

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Declaration of conflict of interest

The authors have collectively contributed to the conceptualization, design, and execution of this journal. They have worked on drafting and critically revising the article to include significant intellectual content. This manuscript has not been previously submitted or reviewed by any other journal or publishing platform. Additionally, the authors do not have any affiliation with any organization that has a direct or indirect financial stake in the subject matter discussed in this manuscript.

References

[1] Okardi, Biobele , Udokike Daniel Ikegbunam (2024). Face Recognition and Identification System for Crime Detection Using Python Programming Language. *Ijraset Journal For Research in Applied Science and Engineering Technology*, https://doi.org/10.22214/ijraset.2024.60813

[2] Singh, S., & Prasad, S. V. A. V. (2018). Techniques and challenges of face recognition: A critical review. *Procedia computer science*, *143*, 536-543.

[3] Menaka, K., & Yogameena, B. (2021). Face detection in blurred surveillance videos for crime investigation. In *Journal of Physics: Conference Series* (Vol. 1917, No. 1, p. 012024). IOP Publishing..

[4] Bakhshi, Y., Kaur, S., & Verma, P. (2015). A study based on various face recognition algorithms. *International Journal of Computer Applications*, *129*(13), 16-20.

[5] A. Pongade, S. Karad, D. Ingale, and S. Mahabare, (2024). Face Detection and Recognition for Criminal Identification System. *International Research Journal on Advanced Engineering Hub (IRJAEH)*, vol. 12, no. 1, pp. 877–883. https://doi.org/10.47392/IRJAEH.2024.0267

[6] Ishabailu, F. (2017). Image Noise Reduction and Filtering Techniques. *Z. Pei.International Journal of Science and Research (IJSR)*, (3)., doi: 10.21275/25031706.

[7] H. Zhu, W. Zhang, H. Tang, and K. E. Zhao (2024). Self-Supervised Real-world Image Denoising based on Multi-Scale Feature Enhancement and Attention Fusion," *IEEE Access*, doi: 10.1109/ACCESS.2024.3384577.

[8] X. Lu, D. Colbry, and A. K. Jain (2004). Matching 2.5D scans for face recognition, *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 3072, pp. 30–36, doi: 10.1007/978-3-540-25948-0_5.

[9] A. K. Singh, S. Kumar, B. Kumar, and A. S. Chauhan (2023). Face Recognition Using Machine Learning, *Int. Conf. Sustain. Emerg. Innov. Eng. Technol. ICSEIET*, 8(4),361–364,doi: 10.1109/ICSEIET58677.2023.10303390.

[10] Gourav and T. Sharma (2017). Various Types of Image Noise and De-noising Algorithm. *Int. J. Mod. Educ. Comput. Sci.*, 9(5) , 50, doi: 10.5815/IJMECS.2017.05.07.

[11] S. Kaur (2015). Noise Types and Various Removal Techniques. *J. Adv. Res. Electron. cs Commun. Eng.*, vol. 4, no. 2, pp. 226–230.

[12] Uzakkyzy, N., Ismailova, A., Ayazbaev, T., Beldeubayeva, Z., Kodanova, S., Utenova, B., Kaldarova, M. (2023). Image noise reduction by deep learning methods. *International Journal of Electrical & Computer Engineering*, *13*(6), pp. 6855~6861

[13] P. K. Rajvor, S. J. Ahmad, S. Yasmin, A. Hasan, and D. Rafi (2022). A review on : Different type of noise model in digital image processing, no. 2, pp. 14–19 .

[14] Karahan, S., Yildirum, M. K., Kirtac, K., Rende, F. S., Butun, G., & Ekenel, H. K. (2016). How image degradations affect deep CNN-based face recognition?. In *2016 international conference of the biometrics special interest group (BIOSIG)* (pp. 1-5). IEEE.

[15] Li, W., Guo, H., Liu, X., Liang, K., Hu, J., Ma, Z., & Guo, J. (2024). Efficient Face Super-Resolution via Wavelet-based Feature Enhancement Network. arXiv. *arXiv preprint arXiv:2407.19768*.

[16] Alisha, P. B., & Sheela, K. G. (2016). Image denoising techniques-an overview. *IOSR J. Electr. Commun. Eng*, *11*, 78-84.

[17] Dabov, K., Foi, A., Katkovnik, V., & Egiazarian, K. (2006, February). Image denoising with block-matching and 3D filtering. In *Image processing: algorithms and*

systems, neural networks, and machine learning , Vol. 6064, pp. 354-365.

[18] K. Berahmand, F. Daneshfar, E. S. Salehi, Y. Li, and Y. Xu (2024). Autoencoders and their applications in machine learning: a survey, *Springer Netherlands*, vol. 57, no. 2. doi: 10.1007/s10462-023-10662-6.

[19] Buades, A., Coll, B., & Morel, J. M. (2011). Non-local means denoising. *Image Processing On Line*, *1*, 208-212.

[20] Preiya, V. S., Vijay, R., Hemlathadhevi, A., & Sri, C. B. (2024). Facial Recognition for Criminal Identification using Convolutional Neural Network. *Fusion: Practice & Applications*, *16*(1), pp. 118–132, 2024.

[21] M. B. Darici and Z. Erdem (2023). A Comparative Study on Denoising from Facial Images Using Convolutional Autoencoder, *Gazi Univ. J. Sci*., 36(3), pp. 1122–1138, doi: 10.35378/gujs.1051655.

[22] Zulkarnain, S. T., & Suciati, N. (2022). Selective local binary pattern with convolutional neural network for facial expression recognition. *International Journal of Electrical & Computer Engineering*, *12*(6).pp. 6724–6735, doi: 10.11591/ijece.v12i6.pp6724-6735.

[23] Hadid, A. (2008). The local binary pattern approach and its applications to face analysis. In IEEE. *First Workshops on Image Processing Theory, Tools and Applications* (pp. 1-9).

[24] L. Zhou, J. D. Schaefferkoetter, I. W. K. Tham, G. Huang, and J. Yan, (2020). Supervised learning with cyclegan for low-dose FDG PET image denoising, *Med. Image Anal.*, vol. 65, p. 101770, doi: 10.1016/J.MEDIA.2020.101770.

[25] Niu, B., Gao, Z., & Guo, B. (2021). Facial expression recognition with LBP and ORB features. *Computational Intelligence and Neuroscience*, *2021*(1), 8828245. https://doi.org/10.1155/2021/8828245

[26] Chandrakala, M., & Devi, P. D. (2021). Two-stage classifier for face recognition using HOG features. *Materials Today: Proceedings*, *47*, 5771-5775.

[27] Fan, L., Zhang, F., Fan, H., & Zhang, C. (2019). Brief review of image denoising techniques. *Visual computing for industry, biomedicine, and art*, 2(1), p.7

[28] Tian, C., Fei, L., Zheng, W., Xu, Y., Zuo, W., & Lin, C. W. (2020). Deep learning on image denoising: An overview. Neural Networks, 131, 251-275.

[29] Goyal, B., Dogra, A., Agrawal, S., Sohi, B. S., & Sharma, A. (2020). Image denoising review: From classical to state-of-the-art approaches. *Information fusion*, *55*, 220-244.

[30] Khasanova, A., Makhmutova, A., & Anikin, I. (2021, May). Image denoising for video surveillance cameras based on deep learning techniques. In IEEE *International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM)* (pp. 713-718).

[31] Tawfik, M. S., Adishesha, A. S., Hsi, Y., Purswani, P., Johns, R. T., Shokouhi, P., ... & Karpyn, Z. T. (2022). Comparative study of traditional and deep-learning denoising approaches for image-based petrophysical characterization of porous media. Frontiers in Water, 3, 800369.https://doi.org/10.3389/frwa.2021.800369

[32] Hardeep Singh, Gagandeep (2022). local binary patterns and its application to facial analysis. *International Journal of Engineering Research and Reviews, 10(3), 11-20, DOI: https://doi.org/10.5281/zenodo.7014367*

[33] Sevakula, R.K., Verma, N.K. (2023). Stacked Denoising Sparse Autoencoder-Based Fuzzy Rule Classifiers. In: Improving Classifier Generalization. Studies in Computational Intelligence, vol 989. *Springer, Singapore*. https://doi.org/10.1007/978-981-19-5073-5_6

[34] Kong, Z., Deng, F., Zhuang, H., Yu, J., He, L., & Yang, X. (2023). A comparison of image denoising methods. *arXiv preprint arXiv:2304.08990*.

[35] Arora, S., Mittal, R., Kukreja, H. et al. An evaluation of denoising techniques and classification of biometric images based on deep learning. Multimed Tools Appl 82, 8287–8302 (2023). https://doi.org/10.1007/s11042-021-11573-w