ENHANCING LOW-RESOLUTION IMAGES THROUGH NOISE FILTERING AND FEATURE PRESERVATION

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ABSTRACT

This paper presents a comprehensive resolution enhancement model to increase the quality and make low-resolution images more detailed and clearer. As a result of, images will appear better visually and any lost or obscured details in the original images will be restored. In fields like computer vision and image processing, it can be challenging to enhance the resolution of low-quality images. However, doing so can make it possible to analyze, interpret, and deploy visual data more effectively to be able to accurately analyze or identify significant features, low-resolution images lack the clarity and detail necessary. Through the process of image enhancement, specialists, researchers, and analysts can find hidden patterns or anomalies, extract more pertinent information, and use enhanced visual data to make better decisions. The proposed model's tasks involve combining steps for image enhancement, filtering, and pre-processing. To prepare the data for post-processing, the Labeled Faces in the Wild (LFW) dataset is loaded and resized during the preprocessing phase. Gaussian and Laplacian filtering are two kinds of filtering techniques that are used to enhance the appearance of images, detect edges, and decrease noise. Laplacian filtering assists in edge detection and feature extraction, while Gaussian filtering reduces noise and maintains image details. In the enhancement stage, the filtered image and the original low-resolution image are combined using image blending techniques to produce an enhanced detail level, sharper edges, and better image quality. metrics SSIM and PSNR are used to assess how effective the proposed model is. The results showed that, across a range of image sizes, the proposed model consistently performs better than recent studies, indicating higher performance in enhancing image quality while maintaining structural information. Furthermore, histograms of various sized images provide clarity on how resizing impacts the distribution of pixel density and general image quality and clarity of the image. The proposed model provides potential for use in computer vision and image processing applications and shows significant progress in low-resolution enhancement of images.

Keywords: *Low-Resolution Image, Image Enhancement, Image quality, ML, Gaussian, Laplacian, LFW*

1. INTRODUCTION

Face recognition has been a particularly active area of computer vision research for a long time. Now, facial recognition systems are widely employed, and their uses are expanding to include mobile device security, retail, and public safety [1]. When compared to voice, fingerprint, iris, retina, eye scan, gait, ear, and hand geometry, face recognition is a very effective method and one of the most used biometric modalities for individual identification and verification. This has forced academic and industrial researchers to develop several types of face recognition algorithms throughout the years, making face recognition one of the most researched areas of computer vision research. Due in large part to its application in unconstrained environments, where most existing techniques do not function optimally, it continues to be a rapidly expanding field of study. These conditions include low-resolution images, poor lighting, ageing, occlusion, expression, and plastic surgery [2]. One of the critical challenges regarding face recognition systems is their low performance, which is mainly due to low-resolution (LR) images. Extracting human facial features from an LR image is becoming increasingly challenging. Less diversity in the LR face image's features is the cause of this. Inaccurate alignment of input face patches and noise from individual variations in size, expression, and pose are some of the main causes of face recognition performance loss on low resolution images [3]. As a result, significant information about every individual's face image is lost. Face recognition systems are impacted by this problem, particularly in surveillance applications. Therefore, it continues to be a problem in face recognition systems when compared to images with a high resolution [2]. The majority of face recognition algorithms currently in use achieve high accuracy in controlled environments, but their performance suffers in low-resolution images [4]. Using filtering methods for low-resolution images, filtering them from noise and distortion, improving their quality,0020and removing disturbances in the image data caused by the effect of noise are important solutions to increase the efficiency of the performance of face recognition systems[5]. Low-resolution images can be enhanced using methods filtering increases the clarity of images, removes noise from them, and extracts important and effective features for the purpose of detecting and recognizing faces in these images[6]. Deep learning algorithms and methods have contributed in recent years to enhancing the performance of face recognition systems because of their effective capabilities in building training and testing models for efficient face recognition by preserving the identity information of the image and extracting the most important features from the images [7]. One of the advantages of using deep learning techniques is that it provides a low-cost solution, less energy consumption, in addition to completing the real-time recognition task with high efficiency [8].

The research will focus on following contraptions:

- Highlights attention to the critical problem that face recognition algorithms have when dealing with low-resolution (LR) images, which negatively affect their performance by limiting the variety of facial features and resulting in information loss.
- Focusing on the most important methods used in filtering and enhancing LR images used in removing noise and distortion, and thus improving their quality.
- Highlighting ML algorithms in improving the performance of face recognition systems to enhance recognition accuracy in LR images.
- There is a need for development in LR image enhancement techniques, as they are of great importance in other advanced fields such as mobile security, retail, and public safety.

2. LITERATURE REVIEW

In various fields, including face recognition and surveillance, low-resolution images represent an essential challenge. The low pixel density of these images frequently results in a loss of visual quality, making them difficult to utilize and interpret. In particular, in surveillance systems, the accuracy of recognizing and differentiating individuals based solely on their appearance is directly impacted by image clarity. Because of this, surveillance systems typically depend on clear images to successfully identify and track objects or identify specific individuals.

The study [9] introduces a new approach called "RIM." To help increase the accuracy of face recognition in low-resolution images, the model uses machine learning techniques as well as deep neural network techniques such as CNN and RNN.Many databases were also used, such as Helen and LFW databases. The SSIM results were 0.882 and PSNR 28.572 for LFW. The study showed how difficult it is to extract important features and details from low-resolution images, and how important it is to preserve the accuracy and clarity of these images while enhancing them. The research [10] focused on enhancing digital image resolution by applying deep learning methods and Convolutional Neural Networks (CNN) to increase image accuracy. To evaluate the results, the B100, Manga109, Set14, Set5, and Urban100 databases were examined. The research obtained results PSNR 0.2894, 0.3253, 0.3001, 0.3393and 0.2774 and SSIM 0.8071, 0.9423, 0.8426, 0.9259 and 0.8504 respectively. According to research, using pre-trained networks can lead to false colors artifacts and slow convergence during training.

The research [11] present a method for enhancing the quality of low-resolution noisy facial images using the MDFR model using the Multi-PIE and CelebA datasets. The results show that the model achieved good performance in improving the quality of facial images and recovering them from low-quality images. Metrics such as PSNR and SSIM were used to evaluate the model performance and in the Multi-PIE dataset, it achieved 27.256 and 0.898, respectively. On the CelebA dataset, the model achieves 27.847 and 0.907 respectively but the method only uses high-quality images to guide feature learning without considering the intertwining effect of different decomposition factors in the feature space, which may reduce the representation ability of the encoded features. The paper [12] discusses the "Face Hallucination" technique which aims to improve the quality of facial images. Different databases are used in the study, for example CMU Multi-PIE and LFW. The results showed that the proposed model achieved PSNR and SSIM in the Multi-PIE database of 32.07 and 0.895, and with LFW, it achieved 31.01 and 0.9149, respectively. Additionally, the proposed method might have trouble restoring fine facial features, which would lower the overall quality of the improved images. The paper [13] offers a proposed strategy that makes use of multi-scale structures and deep learning techniques to improve the resolution of facial images. It use ESEM, PA, and FEM to enhance the network's capacity to extract structural information from the image and Hourglass blocks for feature extraction of important facial areas. The PSNR and SSIM values for the Helen and LFW datasets are 27.744 dB, 0.830 and 29.165, 0.838 respectively. Moreover, the study encountered difficulties in recovering fine details and distortions in the positions of the eyes. The study [14] introduced innovative framework for highly accurate face recognition and image retrieval using SCGAN (Standardised Convolute Generative Adversarial Network) technology. This was accomplished by using methods like Generative Adversarial Network (GAN), Convolutional Neural Network (CNN), and Principal Component Analysis (PCA). Using LFW data, the retrieved faces were recognized with an SSIM of 98% and a PSNR of 18. Low-quality image distributions were a challenge in the process of creating high-quality images. Limitations in face recognition such as blur, noise, diverse facial expressions, and opacity made face recognition difficult. The paper [15] discussed a method called (BFRffusion), whose purpose is to recover facial features from low-resolution images and enhance them. Techniques such as a shallow degradation removal module, multi-level feature extraction module, and a trainable time-aware prompt module. The FFHQ and PFHQ datasets were also used for training and testing. The evaluation metrics used in the paper include PSNR and SSIM to measure the quality of the recovered images, and their values are 24.83, 0.7143 respectively.

The research [16]suggests developing an efficient Crypto General Adversarial neural network for the encryption and decryption process with image enhancement, in addition to using optical chaotic maps for effective encryption and decryption of the image. The research additionally deals with the use of the deep learning GAN technique. The results show a considerable improvement in performance parameters such as PSNR and SSIM by up to 92% and 68%, respectively, using medical pictures, chest X-rays, and the LFW dataset. The paper [15] presents a proposed method for image super-resolution and image drawing tasks. Using a range of technologies such as DFDNet, PSFRGAN, GFPGAN, RestoreFormer, VQFR, CodeFormer, DifFace-100, ResShiftL-4 and others. The databases used for evaluation included LFW, WebPhotoWIDER, and CelebA-Test. The "DifFace-100" approach achieved the best result, which is 24.24 for PSNR and 0.702 for SSIM.

A literature review of recent studies revealed that a variety of methods and techniques have been used to address the challenges faced by facial recognition systems in enhancing the quality of low-resolution images. These challenges are still being studied, such as distortions in key facial features such as eye positions and the difficulty of recovering fine facial details, which It may lead to reducing the overall quality of the images that have been enhanced, in addition to other limitations such as blurring, noise, various facial expressions, and opacity, as these challenges are still considered a major limitation facing enhancing the quality of low-resolution images and facial recognition with high accuracy and efficiency. Therefore, research is still underway to experiment and use innovative methods to mitigate the impact of these challenges, which will reflect positively on enhancing the performance of face recognition systems for low-resolution images.

3. METHODOLOGY

Figures should be labeled with "Figure" and tables with "Table" and should be numbered sequentially, for example, Figure 1, Figure 2 and so on (refer to table 1 and figure 1).

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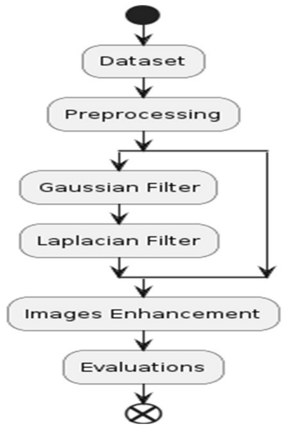

Figure 1: framework for the proposed model.

The proposed model for enhancing the accuracy of low-resolution images consists of the following main stages, as in Figure1, these stages are image pre-processing, image filtering techniques, image enhancement, and finally the model evaluation stage.

4. PREPROCESSING

The pre-processing stage of the data used is considered a very necessary stage before the actual use of this data. This includes the process of preparing the entered data and transforming it from unclean data to clean data ready for application. Pre-processing is done before running the algorithm to search for noisy data, missing values, and other things abnormalities that hinder the work of the algorithm, as the data must be formatted in a way that is compatible with machine learning. The pre-processing phase of the proposed system included two important parts: the dataset loading part and the change in resizing the dataset.

The first part of pre-processing includes loading The Labeled Faces in the Wild (LFW) dataset, where the database consists of a group of classes, and each class includes images of a specific character with the label for that character as a name for the class. As well as the number of classes and their names are known within that dataset.

In the second part, the dataset will be prepared by making changes to the size of the images in the LFW dataset and converting them to a low-resolution dataset for the images within the dataset.

5. FILTERING TECHNIQUES

Noise filtering stage becomes an essential step for enhancing the quality of low-resolution images. For filtering noise for low-resolution images, a filtering method was proposed using a gaussian filter, A common technique for reducing noise and smoothing images is Gaussian filtering, sometimes referred to as Gaussian smoothing or Gaussian blur. Image details can be preserved while Gaussian noise is reduced using Gaussian filtering [17][18]. It operates by using a Gaussian kernel, or two-dimensional Gaussian distribution, to convolve the image. By averaging pixel values inside the Gaussian kernel's defined neighborhood, the Gaussian filter essentially blurs the image. While maintaining crucial visual edges and image structures, this smoothing helps in the reduction of high-frequency noise. By providing a smoother image, applying this filter can assist reduce noise and increase the efficacy of the following processing processes [19].

The second technique that will be used for the purpose of filtering is a Laplacian Filter (sometimes called LoG, or Laplacian over Gaussian filter). In image processing, the Laplacian filter is employed for edge detection. Using this filter can aid in identifying the images' edges and small details [20], which is useful in feature extraction. It is used to locate objects, detect boundaries, and extract features. Finding small, localised changes in the pixel intensity levels inside an image is the aim of edge detection. Using the Laplacian filter, the second derivative of the intensity function of the image is computed [21]. This method shows areas with rapid changes in intensity.

Before using the Laplacian filter, the image is typically smoothed using a Gaussian filter. This pre-processing stage aids in reducing noise and preventing noise from increasing during edge detection. The input (Gaussian image) is first preprocessed using a Laplacian filter. The next step is to apply Adaptive Histogram Equalization (AHE) [21] on the preprocessed image to generate an enhanced output image, as shown in figure 2.

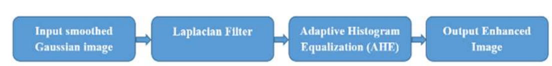

Figure 2: Laplacian filter steps.

6. ENHANCEMENT

To enhance the overall quality of the low-resolution image and increase its clarity in general, an enhancement method will be adopted for this image by blending the outputs of the Laplacian filter (which was originally applied to the outputs of the Gaussian filter, which in turn was applied to the original image) with the original input image using (Image Blending) or (Blending images by weight) method Therefore, the result of this method will be

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to obtain an enhanced image that contains a mixture of information as a result of mixing two images with a different weight for each. This enhancement step is an important step that contributes to sharpening edges and highlighting small details in the reconstructed image. This will reduce noise more effectively and obtain better image enhancement results, thus improving the image characteristics and extracting important features from it [22] [23].

7. EVALUATION METRICS

It's critical to evaluate the enhancement techniques' efficacy objectively when using noise filtering to enhance low-resolution images while maintaining essential features. Evaluation criteria are essential for measuring how well the enhanced images compare to the original, low-resolution ones. Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are two commonly applied evaluation metrics for this purpose.

PSNR: is used to compare an image's quality to the original image that was input. Perceived signal strength to noise ratio (PSNR) measures how well a signal is represented relative to its maximum potential power [24][25].

SSIM: It is a metric for comparing two images, the input image coming from the input and the smoothed image after applying a Gaussian filter. Because it considers the lighting, contrast, and structure of comparable images, this measure is especially helpful for assessing the perceptual quality of images. The SSIM score has a range of (-1) to (1). A number nearer 1 denotes a high degree of similarity between the two images, indicating a high degree of contrast, structure, and detail similarity. This indicates the image enhancing technique applied with the Gaussian filter was effective and did not it have a significant impact on its details and structure, and as the SSIM value gets closer to zero, this indicates that the image's essential information was lost due to poor enhancement techniques [26].

8. LFW DATASET DESCRIPTION

The Labeled Faces in the Wild (LFW) dataset is used in the fields of computer vision and face recognition, LFW is a commonly used benchmark dataset. It includes a collage of different individual faces that were gathered on the internet, with a wide range of poses, expressions, lighting conditions, and backgrounds. Due to the wide range of conditions and contrasts in the images, LFW presents a challenge for the models that rely on face recognition. Approximately 13,233 facial images of more than 5,749 individuals are included in the LFW dataset [27]. For evaluation of the model, high-resolution images from the LFW dataset were resized to match the low-resolution conditions.

9. RESULTS AND DISCUSSION

In this section, the results obtained when applying the steps of the proposed model on LFW dataset are presented, where Gaussian filtering was applied as the first step in the enhancement techniques, and the resulting enhanced Gaussian images show that the PSNR values and SSIM values as shown in Table 1.

Table 1: Enhancement results after applying Gaussian Filter.

Images size	PNSR	SSIM
Original size	40.257	0.987
32x32	30.587	0.891
64x64	32.60	0.932
128x128	35.85	0.969

The second step of the enhancement techniques included Applying the Laplacian filter to the output of the enhanced image resulting from the Gaussian filter, where the PSNR and SSIM results were as in Table 2.

Table 2: Enhancement results after applying Laplacian Filter.

Images size	PNSR	SSIM
Original size	33.749	0.261
32x32	33.756	-0.171
64x64	33.74	-0.014
128x128	33.75	0.137

The third step of the enhancement technique depends mainly on blending the original low-resolution image with the image resulting from the Laplacian filter, where the third step showed superiority. Clearly and better results for the enhancement techniques, as clearly shown in Table 3.

Table 3: Enhancement results for proposed model.

Images size	PNSR	SSIM
Original size	48.140	0.994
32x32	47.80	0.997
64x64	47.97	0.998
128x128	48.090	0.996

Based on the values of Table 3, these results indicate that the proposed model showed promising performance in enhancing low-resolution images. To investigate how resizing impacts the distribution of pixel intensities, the histograms of images of various sizes are visualized as shown in figure 3. It facilitates comprehension of how resizing an image affects its brightness, contrast, and general appearance. Histogram enhances low-resolution image quality by combining image details at different resolution levels to evaluate image quality [26]. An important way to understand how resizing an image affects information content and image quality is to compare histograms of various sizes. A histogram represents the data values in an image with a statistical distribution. Histogram equalization is the process of applying the histogram equalization method to the image after the histogram has been converted into a cumulative distribution function. Image clarity and imaging quality are enhanced as a result of a more evenly distributed dispersion of pixel values [28].

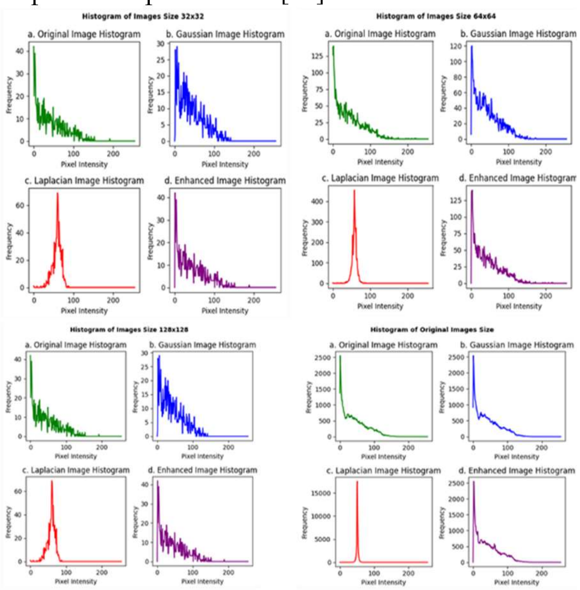

Figure 3: Histograms of Image Intensities for Different Sizes and Processing Methods.

10. COMPARISON WITH RECENT STUDIES

This section provides a comparison and explanation of the results based on the results presented for different image sizes and compares them to other recent studies according to the metrics used to evaluate the model's performance. For all image sizes, the proposed model consistently performs better than any other study with respect to both PSNR and SSIM. The proposed model outperforms previous studies in terms of PSNR and SSIM values, demonstrating a better improvement in image quality. The high SSIM values of the proposed model demonstrate how well it retains structural details and information in images, producing visually attractive results. As a result, shown in table 4, the proposed model's higher PSNR and SSIM values show its most recent capabilities for enhancing images of various sizes.

Table 4: Comparing the proposed approach for enhancing images with the state of art.

Sizes & Metrics / Ref. & years	Original size		32x32		64x64		128x128	
	PNSR	SSIM	PNSR	SSIM	PNSR	SSIM	PNSR	SSIM
[29], 2021	-	-	29.49	0.792	-	-	-	-
[28], 2022	27.57	0.8243	27.49	0.821	27.62	0.825	27.57	0.8246
[27], 2023	-	-	-	-	-	-	31.07	0.94
[26], 2023	39.39	0.9894	-	-	-	-	-	-
[30], 2024	45.38	0.994	-	-	-	-	47.39	0.993
[31], 2024	-	-	29.49	0.792	-	-	-	-
Proposed model	**48.14**	**0.9947**	**47.80**	**0.999**	**47.97**	**0.998**	**48.09**	**0.996**

Based on PSNR and SSIM values across various image sizes, the proposed approach significantly outperforms recent studies in low resolution image enhancement.

11. CONCLUSION AND FUTURE WORK

Compared with recent studies in the field, the proposed model for enhancing low-resolution images performs better. The proposed model efficiently tackles the issues related to low-resolution images by utilizing an all-encompassing strategy that includes preprocessing, filtering techniques, and image enhancement. During the preprocessing phase, the low-resolution dataset the Labelled Faces in the Wild (LFW) dataset is created by loading and resizing the images. This stage makes sure that the data is structured correctly and works with the other processing phases. To reduce noise and detect edges, filtering techniques such as Gaussian and Laplacian filtering are essential. Laplacian filtering enhances edge detection and feature extraction, while Gaussian filtering reduces noise and preserves image features. The model efficiently prepares the images for enhancement by combining several filtering techniques. Image blending techniques are used in the enhancement stage to combine the original low-resolution image with the Laplacian filter image. Enhanced image qualities and feature extraction follow from this step, which also sharpens edges and accentuates very small details. The effectiveness of enhancement techniques is objectively assessed using evaluation measures SSIM and PSNR. Increased PSNR and SSIM values show that the proposed model performs consistently better than earlier research at different image sizes. This suggests that while maintaining structural details and information, the suggested method successfully enhances image quality. Furthermore, seeing the histograms of images of varying sizes helps to understand how resizing affects the distribution of pixel intensities and the general quality of the image. Histogram equalization ensures a more uniform distribution of pixel values, improving image clarity and quality. The proposed model shows notable progress in improving low-resolution photos and has potential for use in computer vision and image processing applications.

Future directions of the paper include focusing on using state-of-the-art deep learning techniques to extract the more relevant features from enhanced images and classify them for optimal face recognition in low-resolution images.

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