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"Enhancing Low-Resolution Images: A Review Of Deep Learning Approaches"

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Abstract-
This paper provides an overview of deep learning-based methods for enhancing low-resolution images. We explore the evolution of deep learning techniques in this context, from early approaches like CNN to state-of-the-art architectures. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in up scaling low-resolution images, effectively capturing intricate patterns and textures. We discuss the underlying principles of these DL-based approaches, highlighting their ability to leverage contextual information and learn complex image representations. Additionally, we delve into the various loss functions and training strategies used to optimize network performance. Applications of deep learning-based super-resolution extend to diverse domains, such as improving the quality of medical scans, enhancing surveillance footage for forensic analysis, and refining satellite imagery for better environmental monitoring. We showcase the potential impact of DL-based super-resolution in these real-world scenarios.
The review paper on low-quality images offers a comprehensive and insightful exploration of the challenges, advancements, and applications in the realm of image enhancement using deep learning. Through meticulous research, the authors have delved into the diverse facets of this field, illuminating the critical role played by deep learning architectures such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) in elevating the quality of low-resolution images. With a keen focus on inclusion and exclusion criteria, the paper synthesizes a wealth of literature, providing a holistic view of the subject. It skillfully navigates through data analysis, presenting quantitative and qualitative assessments of image improvements while illuminating the study's purpose in revolutionizing image perception across industries. Overall, this review paper serves as an invaluable resource, shedding light on the transformative potential of deep learning in addressing the challenges posed by low-quality images in the digital age.
Keywords: *image super-resolution; deep learning; remote sensing; model design; evaluation methods*

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I. INTRODUCTION

In the digital age, images play a pivotal role in communication, analysis, and decision-making across various fields, including computer vision, medical imaging, surveillance, remote sensing, and entertainment. However, not all images are captured or acquired at high resolutions. Low-resolution images, characterized by a limited number of pixels, often lack essential details, hindering their effectiveness in these applications. The challenge posed by low-resolution images has prompted significant research and innovation in the field of image processing. Among the various approaches developed to address this challenge, deep learning has emerged as a groundbreaking solution. Deep learning, a subset of artificial intelligence (AI), has demonstrated remarkable capabilities in enhancing the quality and resolution of images.This paper focuses on the critical role of deep learning in the realm of low-resolution image enhancement. It explores the evolution of deep learning techniques for super-resolution, a process of generating high-resolution images from their low-resolution counterparts. We delve into the underlying principles, methodologies, and applications of deep learning-based super-resolution, highlighting its potential to revolutionize image enhancement. The significance of this topic lies in its relevance across a wide spectrum of industries and domains. For instance, in medical imaging, the ability to upscale low-resolution scans can improve diagnostic accuracy. In surveillance, enhancing low-quality footage can aid in forensic investigations. In satellite imaging, sharpening low-resolution satellite photos can advance environmental monitoring and disaster management.

Throughout this paper, we will journey through the landscape of deep learning-based super-resolution, uncovering its principles, methodologies, applications, and future prospects. We will explore the techniques employed in training deep neural networks to recover intricate image details and provide insights into the evolving trends within this dynamic field. Ultimately, we will showcase how deep learning is transforming the way we perceive and utilize low-resolution images in the digital age.

Each person has a unique face, and the human brain seems to be able to use this feature to recognize people. Automatically recognizing human faces, on the other hand, has become a big problem in the last 20 years because there are so many real-world apps that need this ability. Face recognition, or FR for short, is a way to easily identify or verify a person's identity based on an image of their face. The most common way to do this is to compare a picture of an unknown person, called a "probe image," with a large collection of pictures of likely suspects, called a "gallery," and then match the probe image with the picture in the gallery that looks the most like it. Human face recognition study has gotten a lot more popular in recent years, mostly for two reasons. The first reason is the wide range of commercial and law enforcement uses, and the second is that the problem of machines recognizing human faces has drawn researchers from many different fields, including image processing, neural networks, computer vision, pattern recognition, and psychology [1]. First, there are a lot of business and law enforcement uses for it, and second, there are a lot of law enforcement uses for it. Even though there are many reliable ways to use biometrics to identify a person, like scanning the retina or iris or looking at fingerprints, these systems need the help of both the person being named and the identification system to make accurate decisions. In addition, the database for these kinds of recognition tools is not easy to use. Because of this, most people think that facial recognition has a lot of untapped potential to make automatically identifying humans easier. These three sources give a thorough and insightful look at face recognition systems: [2][3].

Face recognition is hard for machines to do in the real world, where pictures may be taken in a chaotic setting. Many of FR's problems, such as bad lighting, different poses, and big changes in how people look, have been fixed. But face recognition is still hard to do in many real-world settings, like with video security cameras, where it's hard to get good recordings of people's faces. How good the records are can be judged in part by how clear the pictures are. Usually, the pictures are not clear enough to be used for normal face recognition. So, it's becoming very important to figure out how well FR systems work when the picture resolution gets smaller and to try to improve the resolution of low-resolution (LR) images. The goal of this study is to find out how well different face recognition methods work when the picture resolution changes. It also tries to improve the quality of the pictures sent in so that better performance can be reached [4].

Face Recognition System: There have been many different proposals for algorithms to perform face recognition, and each one takes a somewhat different approach. Nevertheless, each one of them utilizes a flowchart that is conceptually analogous to the one presented in figure 1. In the following paragraphs, each stage of the recognition system will be broken down, and specific examples of the processes that must be carried out at each stage will be provided.

Image pre-processing: At this point, the image is subjected to a number of different procedures that, collectively, serve to improve its overall quality. The following is a condensed version of the pre-processing stages that are utilized the most frequently.

Histogram equalization. When photos are taken in a place where there aren't many rules, it's important to improve both the picture quality and the performance of face recognition algorithms so that they can deal with images that are too bright or too dark. Histogram equalization is a way to improve classification by smoothing out the histogram of pixel intensities in an image, as shown in figure 1.

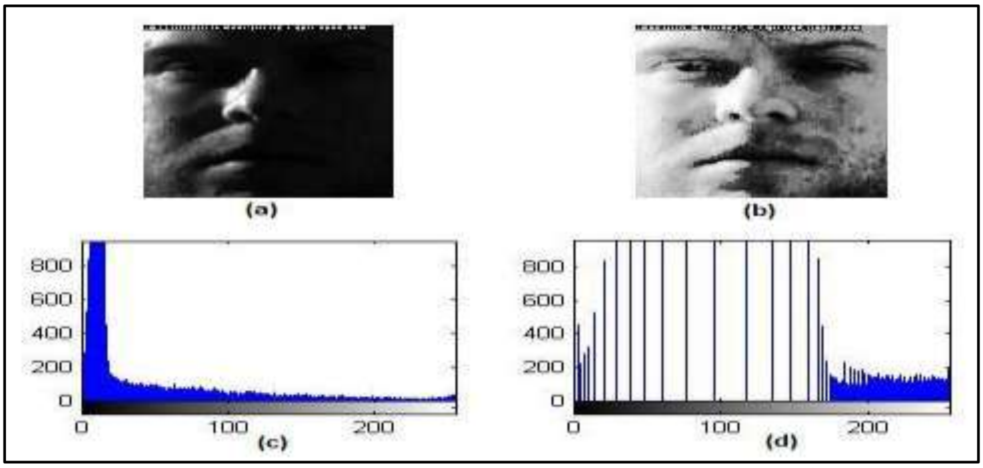

Figure 1.: Equalizing a histogram. a) Image with bad lighting. b) The picture after the histogram was balanced. Histograms of pictures (a) and (b) are (c) and (d), respectively.

Image size normalization. In some applications of face recognition, the input image must be changed to a standard size for the face recognition engine to get the best possible result. In apps where the face images are looked at as a whole, this is the case [5].

- **Median filtering.** Images that have been acquired may on occasion display some noise as a result of either the camera or the environment. In this instance, a median filter is utilised to clean up the image while preserving an adequate level of detail.
- **High-pass filtering**. This form of preprocessing is utilized in recognition systems in which the feature extractors are based on the local features and contours of the image. This kind of preprocessing is typically required even when the photographs being inputted are of a high grade.
- **Translational and rotational normalizations**. Images of people's faces are expected to be frontal in the conventional face recognition system so that the system can achieve a high level of accuracy. However, in many real-life situations, the subject is not cooperative with the acquisition system. In this scenario, the preprocessing stage is required to either change the face position in order to get the frontal view or determine and normalize the rotation.

Illumination normalization. The pixel value is a reflection of the brightness on the unit area at that particular place on the facial region. Indeed, the pixel values have an immediate impact on the accuracy of face recognition algorithms that are based on comprehensive feature extraction. When a face is photographed under a variety of lighting conditions, the entries of the face image array that is used to represent the face in the system can dramatically shift, which can result in a reduction in the accuracy of the face recognition system's ability to identify the subject. Therefore, illumination normalization is essential in order to impose homogeneous lighting on the image.

Feature Extraction Module: After the image of the face has been processed to improve its quality and position, it is sent to the next stage, where the possible features are extracted. There are a few different ways to separate features, and picking the right one is still a question that needs to be answered. There are mainly two types of feature extractors, which are called geometric or local feature extractors and holistic or global feature extractors. The first one looks at the structure of the face and pulls out geometrical and structural features, like the shapes of the eyes, nose, mouth, and chin, as well as the lengths between each of these features. The second type takes the whole picture and pulls out information from each pixel. In the third chapter, there will be a more in-depth discussion of this process.

Classification: A feature vector is displayed as a result of the extraction of the most distinguishable features from the facial image, and it is then supplied into the classification process. During the training phase of this classification module, all of the face image representations that have been saved in the face library (database) are matched and compared to the facial representation that has been provided. The unidentified image is then matched to the image in the face space that is the closest match, and the class of the unknown image is decided. The training set is a collection of different pictures of people's faces that are utilized throughout the training phase of the process of face recognition. The feature extractor and the classifier both require that this process be carried out in order to adjust and optimize their respective parameters.[6] It's possible that erroneous categorization will result from using a limited number of training samples. On the other hand, making use of a very large database could result in overfilling if the examples in a particular category are extremely comparable to one another. Additionally, it extends the amount of time required for the majority of the recognition systems. There are some configurations of face recognition that do not require a training step. Following the successful classification of the "unknown" input image, the image is then added to the samples of its class that are stored in the library for further comparison.[7]

Problem of Face Recognition from Low Resolution Image

The main things that affect how well a face recognition system works are a number of different factors that can affect how well the face is represented. Some of these things are the way the face is lit, how old it is, how it looks, what it is worn on the face, how much hair it has, and how big the face looks. Based on these problems, face recognition could be split into two groups based on how helpful the person is. The first kind of group is the user association. In this case, the user is ready to show him or herself to the camera or the computer in a number of ways. Access control and computer passports are two examples of these kinds of uses.

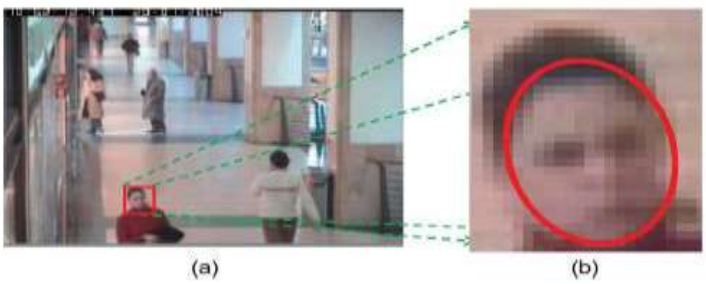

Figure 2: Capturing a face from a surveillance video. a) Surveillance video, b) Facial region

The end result is face recognition in a controlled environment, in which the face is presented in an appropriate manner. For instance, the frontal image should have a high resolution, the lighting should be under control, and the expression should be natural. Figure 1.3 depicts one of the most typical places where the non-cooperative user face recognition occurs: in surveillance applications. When using these kinds of applications, the user is completely ignorant that they are being recognized by the system. As a consequence of this, the recognition of uncontrolled environments is utilized [8]. This kind of face recognition application is plagued by the difficulties described earlier, one of which is that the objective face is situated at a considerable distance from the camera, which results in the face image having a low resolution. There are further applications that fall somewhere in between the two categories that have been discussed above. Considered to be the correct one by the classification system.

II. RESEARCH METHODOLOGY

The present systematic review aims to provide a survey of different machine-learning& deep neural network techniques used in the identification of rice plant diseases based on images of infected rice plants. The methodology of review consists following steps:

1. Data Collection
2. Searched databases

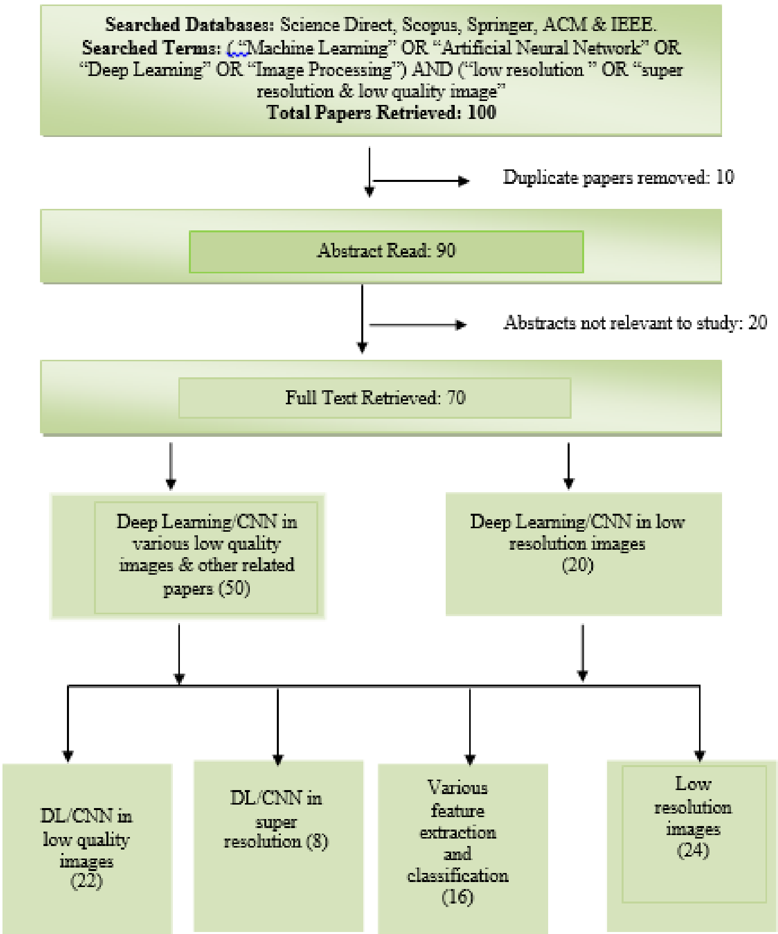

Figure 3: Research Methodology Flow

Five databases were used for the analysis of this literature: Science Direct, Scopus, Springer, ACM (Association for Computing Machinery) and IEEE (Institute of Electrical and Electronic Engineers) (IEEE Explore Digital Library). The time interval used in this survey was defined from 2015 to 2020.

Searched Terms:

When conducting a study on improving low-quality images using deep learning, researchers might use specific keywords and phrases to search for relevant literature. Some potential search terms could include:

- Low-resolution images
- Image enhancement
- Super-resolution
- Deep learning for image improvement
- Neural networks for image quality enhancement
- Image restoration with deep learning

Inclusion Criteria: Inclusion criteria are the specific characteristics or attribute that research studies consider when selecting articles, papers, or data for analysis. In a study on improving low-quality images, inclusion criteria might include:

- Studies that utilize deep learning techniques.
- Research focused on image enhancement or super-resolution.
- Studies published within a certain time frame.
- Papers available in specific languages or from particular sources.

Exclusion Criteria: Exclusion criteria are used to filter out irrelevant or low-quality sources from the study. For improving low-quality images using deep learning, exclusion criteria might include:

- Studies not related to image enhancement.
- Research lacking deep learning methods.
- Studies with poor experimental design or methodology.
- Articles from non-peer-reviewed sources.

Data Analysis: Data analysis in such a study involves examining the results of experiments or case studies related to improving low-quality images using deep learning. This may include:

- Quantitative analysis of image quality metrics (e.g., PSNR, SSIM).
- Qualitative assessment of visual improvements..
- Data visualization to present findings effectively.

Purpose of the Study: The purpose of a study on improving low-quality images using deep learning is to investigate and demonstrate the effectiveness of deep learning techniques in enhancing the quality of images. The study aims to provide insights into which methods are most effective and under what conditions.

Deep Learning Architecture: In a study focused on improving low-quality images, researchers may explore various deep learning architectures specifically designed for image enhancement. Some common architectures for this purpose include:

- Convolutional Neural Networks (CNNs).
- Generative Adversarial Networks (GANs) for super-resolution.
- Autoencoders for image denoising and restoration.
- Recurrent Neural Networks (RNNs) for sequential data, which might be applicable in video enhancement.

III. LITERATURE REVIEW

Face recognition from Low Resolution Images

Currently typical face recognition systems usually require face images with more than 50 pixels between the eyes. Due to the high demand for recognizing human faces from low resolution images, many works have been done to address face recognition from smaller images. Experimental studies [9] showed that minimum face image resolution between 32×32 and 64×64 is required for existing algorithms. Boom et al inuse PCA and LDA based face recognition and claim that their approach can give good results on 19×17 pixels. [10] the relation between face recognition rate and face image resolution using two global face recognition algorithms(PCA and LDA) on the AR-face database where a threshold resolution of 64× 48 is observed. Also, the work in [11] demonstrates that the LBP features are discriminative and robust over a range of facial image and it outperforms Wavelet transformer at resolutions down to 14×19 pixels. In [12] it is claimed that PCA/LDA-based system are not very sensitive to resolution and still give good results at resolutions as low as 32×32 pixels. They also claimed that the number of PCA components depends much more on the dataset that is used than on the resolution. Lastly, in [13] claimed that the resolution used for performing face recognition resolution should be less than the resolution that is required to localize the facial landmarks.

We notice that these works do not give enough insight about the impact of the image resolution on different face recognition systems. A few feature extraction methods are presented in this literatures and the impact of the resolution variation on this methods is demonstrated separately. Therefore, part of our work demonstrates in an informative way the performance of different and popular face recognition systems against the resolution variation of the training and testing images. The experiments are designed in a way for comparison results and remarks to be obtained.

Deep-Learning-Based Methods

Daniel Schulz et.al. (2022): Developed a No-Reference method for assessing the quality of ID card images using face and text quality assessment. Created a private dataset of Chilean ID cards for evaluation. Showed that improving image quality leads to better face and text verification performance.[14]

Ang Li Jian Hu et.al. (2022): Proposed a novel Attribute-Conditioned Face Swapping Network (AFSNet) for generating high-quality face-swapped images. Addressed issues of maintaining detail attributes and handling low-resolution images. Used an Image Enhancement Network (IEN) and a Face Exchange Module (FEM) for improved results.[15]

Qiye Lian et.al. (2022): Introduced an unsupervised Face Image Quality Assessment method called VLC-FIQA. Assessed image quality based on the variance of local contribution. Outperformed state-of-the-art approaches on LFW dataset.[16]

Sebastián González et.al. (2022): Investigated the use of Face Image Quality Assessment in Presentation Attack Detection (PAD) systems for ID cards. Employed MagFace, a quality-aware face recognition method, for improved performance.[17]

Weisong Zhao et.al. (2022): Addressed the challenge of masked faces due to COVID-19 using a consistent sub-decision network. Proposed methods for handling masked face recognition datasets and mitigating information loss.[18]

Biying Fu et.al. (2022): Developed tools for explaining unsupervised face image quality assessment decisions and their impact on face recognition. Focused on the behavior of face recognition models with different quality images.[19]

Qiyu Wei et.al. (2022): Utilized StyleGAN to generate high-resolution face images with desired attributes. Trained an attribute classifier to control generated face attributes effectively.[20]

Peng Zheng et.al. (2022): Proposed a Multi-Degradation Face Restoration (MDFR) model for unconstrained face recognition. Addressed challenges such as large pose, bad illumination, low resolution, blur, and noise.[21]

Ying Tai Feida Zhu et.al. (2022): Presented a method for blind face restoration to reconstruct high-quality images from low-quality inputs. Integrated shape restoration and generative priors for realistic facial details.[22]

M. Benedict Tephila et.al. (2022): Proposed a method for enhancing underwater images, addressing issues like low visibility and color cast. Applied subinterval linear transformation, Gaussian low-pass filtering, and bi-interval histogram techniques. Spectral Mixing Analysis-Based Methods Various approaches in spectral unmixing and image fusion, involving sparse matrix decomposition and non-negative matrix factorization. These methods aim to improve the spatial and spectral resolution of remote sensing images, especially hyperspectral data.

In recent years, the SR problem for natural images has made great progress, thanks to the increasing popularity of CNNs.[23]

[24]first proposed a CNN-based approach for natural image SR. After that, scholars successively proposed several novel CNN models to improve the natural image SR performance. All these works show that the design of the network architecture is a key factor that affects the image reconstruction effect. However, unlike natural images, HSIs consist of hundreds of spectral bands, and feature extraction for such high-dimensional 3D data is more difficult to work with. Secondly, it is important for HSI SR to ensure the spectral fidelity of the reconstructed images while improving the spatial resolution for better subsequent spectral decoding work.

The above reasons predestine HSI SR to be a more difficult task. From the current research status, typically, there are two means of enhancing the spatial resolution of HSI: fusion with other high spatial resolution images and single image SR. Fusion-based SR techniques can acquire more external prior information, and the reconstructed images usually have finer textures. Single-image-based SR techniques do not require any other auxiliary image, and have better feasibility in practice. From some early models proposed in 2017 to the blossoming of various strategies today, more and more scholars have devoted themselves to the field of hyperspectral SR reconstruction. In this section, we will respectively introduce the basic components, representative works and future directions of DL-based methods.[25]

Image Quality Assessment

As a visual task, reasonable image evaluation metrics are required for measuring the performance of the model. HSI quality assessment typically starts from the visual effect of the image and makes objective evaluation of the structure and spectral fidelity of the observables. Although the mainstream objective evaluation metrics at this stage often do not match the actual human visual perception, as a simpler and less time-consuming evaluation method compared with subjective evaluation, objective evaluation is often the primary choice of researchers when evaluating images.[26] Several of the most frequently used objective evaluation metrics are introduced in this section. Image Quality Assessment (IQA) metrics are used to quantitatively measure the quality of an image in comparison to a reference image. These metrics help evaluate the fidelity of an image after various image processing operations or compression. Some commonly used IQA metrics include:

PSNR (Peak Signal-to-Noise Ratio): PSNR measures the quality of an image by comparing it to a reference image in terms of signal-to-noise ratio. It is calculated as:

PSNR = 10 * log10((MAX^2) / MSE) (1)

Where MAX is the maximum possible pixel value (e.g., 255 for an 8-bit image) and MSE (Mean Squared Error) represents the average squared difference between corresponding pixels in the original and distorted images.

RMSE (Root Mean Square Error): RMSE is a metric that calculates the square root of the mean squared differences between the pixels of the original and distorted images.

It is calculated as:

RMSE = sqrt(MSE) (2)

SSIM (Structural Similarity Index): SSIM measures the structural similarity between the original and distorted images by comparing luminance, contrast, and structure. It returns a value between -1 and 1, where 1 indicates perfect similarity. The formula is complex but includes terms for luminance, contrast, and structure comparisons.

MAE (Mean Absolute Error): MAE measures the average absolute difference between corresponding pixels in the original and distorted images. It is calculated as:

MAE = (1 / N) * Σ|I_original - I_distorted| (3)

Where N is the total number of pixels in the image.

Traditional Methods

Constrained by the imaging capability of sensors, hyperspectral remote sensing data generally have the problems of long revisit cycles and low spatial resolution. Through HSI fusion technology, the spatial information of high spatial resolution images can be used to effectively improve the spatial resolution of HSI. Unlike MSI fusion, the fusion technology for hyperspectral data requires improving the spatial resolution of images while preserving the spectral features of the original data as much as possible, to meet the application requirements of subsequent spectral interpretations. The current mainstream fusion algorithms for SR reconstruction of HSI can be mainly classified into three categories: based on wavelet transform (WT), based on maximum a posteriori (MAP) estimation, and based on spectral mixing analysis (SMA). Each of these categories are introduced separately in the following sections.[27]

Wavelet Transform-Based Methods

WT is an important transform analysis method in the field of information processing. In the same way that the Fourier transform can decompose a signal into sine waves of different frequencies, WT decomposes an image signal into a set of wavelets by stretching and translating the original wavelets. The multi-resolution decomposition capability is its non-negligible feature, in which the information of the target image is stripped from coarse to fine, layer by layer, in the transform, which can be commonly understood as the function of high-pass and low-pass filters. The method based on 2D WT was first proposed to fuse hyperspectral and multispectral data by [28]. The final generated image has both the spectral resolution of the hyperspectral image and the spatial resolution of the multispectral image by fusing two bands of hyperspectral image with one band of multispectral image. Due to the three-dimensional characteristic of hyperspectral data, [29] proposed an image fusion method based on the 3D WT. Unlike panchromatic images or RGB images, the spectral dimension information is especially important for HSI, and the 3D WT can make good use of the spectral dimension information of images in order to generate fused images of higher quality. As more and more researchers focus on the advantages of WT in the field of SR, Zhang, et al. [30] proposed implementing a Bayesian estimation of hyperspectral images in the wavelet domain, and this method exhibits a high degree of noise immunity while producing reliable fusion results. Without considering the spatially varying point spread function (PSF), [31] proposed using estimated wavelet filter coefficients to learn high-frequency details in the wavelet domain and then use sparsitybased regularization to obtain the final SR image, which enhances the spatial information of the image with almost no loss of spectral information. Since the WT-based method can focus on arbitrary details of a given signal, its potential in the field of image processing is being explored continuously. It is worth noting that the spectral and spatial resampling methods largely determine the quality of the images reconstructed using this method.

MAP-Based Methods

MAP-based methods, which stand for Maximum A Posteriori estimation, are a fundamental concept in Bayesian statistics. They are used for estimating the most likely value of an unknown quantity, given observed data and prior information about that quantity. MAP estimation is a natural extension of Maximum Likelihood (ML) estimation, but it incorporates prior knowledge or beliefs about the parameters being estimated.

In Bayesian statistics, you have a posterior distribution, which represents your updated beliefs about the parameters of interest after observing data. The MAP estimate is the value of the parameter that maximizes this posterior distribution. Mathematically, it is expressed as:

MAP Estimate=arg max (|)MAP Estimate=argmax$\theta P(\theta|D)$(4)

Where:

- θ represents the parameter of interest that you want to estimate.
- D is the observed data.
- (|)$P(\theta|D)$ is the posterior probability distribution of the parameter given the data.

In this formula, you are finding the value of θ that maximizes the posterior probability. This means you are looking for the most likely value of the parameter θ given both the data and any prior information or beliefs you have about θ.Comparing MAP estimation with ML estimation:

1. **Maximum Likelihood (ML) Estimation:** In ML estimation, you seek the value of θ that maximizes the likelihood function, (|)$P(D|\theta)$, which measures how well the data fits the model for different values of θ. ML does not incorporate prior information; it only considers the likelihood of the observed data.
2. **Maximum A Posteriori (MAP) Estimation:** In MAP estimation, you incorporate prior information by multiplying the likelihood function,)$P(D|\theta)$, by the prior probability distribution of θ, $P(\theta)$. This incorporation of prior information leads to regularization, as you are essentially adding a penalty term based on your prior beliefs about θ. The MAP estimate takes both the data and prior information into account.[32]

Table 2 PSNR/SSIM of some representative methods for remote sensing image super-resolution

Models	Method	Scale	Dataset	PSNR/SSIM
LGCnet [55]	combination of local and global Information	×2 ×3 ×4	UC Merced	33.48/0.9235 29.28/0.8238 27.02/0.7333
RS-RCAN [56]	residual channel attention	×2 ×3 ×4	UC Merced	34.37/0.9296 30.26/0.8507 27.88/0.7707
WTCRR [57]	wavelet transform, recursive learning and residual learning	×2 ×3 ×4	NWPU-RESISC45	35.47/0.9586 31.80/0.9051 29.68/0.8497
CSAE [58]	sparse representation and coupled sparse auto encoder	×2 ×3	NWPU-RESISC45	29.070/0.9343 25.850/0.8155
DRGAN [59]	a dense residual generative adversarial	×2 ×3 ×4	NWPU-RESISC45	35.56/0.9631 31.92/0.9102 29.76/0.8544
MPSR [60]	enhanced residual block (ERB) and residual channel attention group(RCAG)	×2 ×3 ×4	UC Merced	39.78/0.9709 33.93/0.9199 30.34/0.8584
RDBPN [61]	residual dense back projection network	×4 ×8	UC Merced	25.48/0.8027 21.63/0.5863
EBPN [62]	enhanced back-projection network(EBPN)	×2 ×4 ×8	UC Merced	39.84/0.9711 30.31/0.8588 24.13/0.6571
CARS [63]	channel attention	×4	Pleiades1A	34.22/0.93371
Fe Net [64]	a lightweight feature enhancement network)	×2 ×3 ×4	UC Merced	34.22/0.93371 29.80/0.8481 27.45/0.7672

Other than the above three mainstream strategies, scholars have also tackled the HSI SR problem from other perspectives. The lightweight network proposed by [33] captures high-frequency details in each band by learning the residual images. To improve the spatial resolution while paying more attention to the spectral information, [34] proposed the ConvDeconv framework based on 3D convolution and imposed additional constraints on the network through end element similarity. [35] First learned the mapping relationship from LR MSI to LR HSI through the constructed self-supervised network SSRN, and then transplanted this relationship into HR MSI and HR HSI mapping. CNN-based models can only mine information and correlationsunder limited sensory fields. To better focus on global information, [36] made the first attempt to use the transformer structure to solve the HSI SR problem and showed excellent performance. In addition, there are still many typical works that have contributed greatly to the progress in this research area [37-38].

IV. CONCLUSIONS

In this paper, we have explored the intricate landscape of face recognition systems, shedding light on the remarkable advancements and evolving challenges in this domain. Face recognition, or FR, holds significant promise and has become a critical technology across various fields, including computer vision, security, law enforcement, and commercial applications. The human ability to effortlessly recognize faces has driven the need for machines to replicate this capability, and researchers from diverse fields have converged to tackle this complex problem. We have discussed how advancements in image processing and deep learning have revolutionized the enhancement of low-resolution images. The ability to upscale low-quality images holds vast potential in fields such as medical imaging, surveillance, and satellite imaging, where image clarity is often compromised. Deep learning, as a subset of artificial intelligence, has emerged as a groundbreaking solution for super-resolution, the process of generating high-resolution images from low-resolution counterparts. This technology has the potential to reshape image enhancement across various industries. Face recognition is a complex problem, particularly in real-world scenarios with variations in lighting, poses, and image quality. While significant progress has been made in addressing these challenges, there is ongoing research to improve face recognition in chaotic settings, such as video security cameras. We have highlighted the critical role of image preprocessing in face recognition. Techniques like histogram equalization, image size normalization, median filtering, high-pass filtering, and translational/rotational normalizations are essential to improve image quality and feature extraction. Feature extraction plays a pivotal role in recognizing faces. Geometric (local) and holistic (global) feature extractors are two common approaches. Extracted features help characterize facial structures and other distinguishing attributes. Classification, the final step in face recognition, involves matching feature vectors with known representations in a face library. Training sets, databases of known faces, and classifiers are crucial components of this process. Accuracy in classification depends on both training data and classifier parameters. In conclusion, face recognition remains a dynamic and challenging field, with real-world applications spanning security, law enforcement, commercial industries, and more. Ongoing research endeavors aim to enhance the accuracy and robustness of face recognition systems, making them increasingly valuable in diverse contexts. As technology continues to evolve, the boundaries of what is possible in face recognition are continually pushed, offering new opportunities and advancements in the field.

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