Chapter 12

Comparison of the Theoretical and Statistical Effects of the PCA and CNN Image Fusion Approaches

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ABSTRACT

An image plays a vital role in today's environment. An image is a visual representation of anything that can be used in the future for recollecting or memorizing that scene. This visual representation is created by recording the scene through an optical device like a camera or mobile phone. The image fusion process helps integrate relevant data of the different images in a process into a single image. Image fusion applications are wide in range, and so is the fusion technique. In general, pixel, feature, and decision-based techniques for picture fusion are characterised. This study's main thrust is the application and comparison of two approaches to the image fusion process: PCA (principal component analysis) and CNN (convolutional neural network).The study implemented a practical approach to MATLAB. The result of the study is that CNN is much more favorable in terms of image quality and clarity but less favorable in terms of time and cost.

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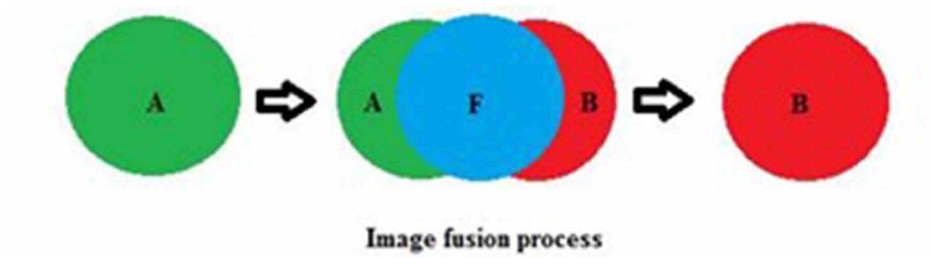
1. INTRODUCTION

Images are created when something, such as a person, thing, place, etc., is portrayed visually. Depending on the frames taken and projections maintained, images may be 2D or 3D. A 3D image is a compilation of several 2D images at various projection levels and angles. 2D images are still pictures. In general, the phrase "fusion" refers to a method of extracting data from multiple sources. In order to create a new image with information of a quality that can only be achieved this way, picture fusion (IF) tries to merge complementary multisensor, multitemporal, or multiview data.

Figure 1. Image fusion process



The definition of quality, how it is measured, and how it is used vary depending on the application. The goal of the Image Fusion method is to gather all the important information from various photographs and combine it into a small number of images, usually just one. Compared to any other image from a single source, a single image is more accurate and informative and has all the necessary information. The goal of picture fusion is to create images that are better suited for human and mechanical perception, not just to reduce the number of records.In essence, two pictures or more of a single scene are combined to create a Single photo, with the best data characteristics of all the images used. An important step and a prerequisite for image fusion is geometry and feature matching of the input images. The growing availability of space-based sensors in distant sensing applications inspires various picture fusion algorithms.

Depending on the particular purpose, many sorts of images can be fused. Some common sorts of photos that are frequently fused are listed below:

a) Hyperspectral or multi-spectral Images: Including the visible, infrared, and ultraviolet spectrums, these photographs record data from a variety of electromagnetic spectrum bands. Utilising fusion techniques, the spectral data from these photos can be combined, enhancing the overall information or increasing the accuracy of the categorization.
b) Images with Thermal Infrared and Visible Light: Combining thermal infrared photographs with images with visible light can give a more thorough understanding of the scene in applications like surveillance or search and rescue. The thermal data can be overlaid on the visible image using image fusion techniques, improving item recognition or detection.
c) Images with a high dynamic range (HDR): These images can capture a wide range of luminosity, from light highlights to deep shadows. With the help of image fusion, it is possible to build an HDR image with improved details and a wider dynamic range by combining multiple photographs taken at various exposure settings.

d) Medical Images: In the field of medical imaging, several modalities like computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) can capture various features of the same patient. Through the use of image fusion algorithms, data from multiple modalities can be combined to provide doctors with a more thorough and precise diagnosis.
e) Panoramic Images: Panoramic images are created by stitching together several photographs taken from various angles. A high-resolution panoramic image with a consistent visual style can be created by using image fusion algorithms to integrate the overlapping sections between photographs flawlessly.
f) Satellite or Surveillance Images: Image fusion can be used to merge images taken by several sensors or at various times in applications like surveillance or satellite photography. The capabilities for object detection, tracking, and change detection may be enhanced by this fusion.
g) Multiresolution Images: Images that have been created or processed at different scales or resolutions are referred to as multiresolution images, also known as multi-scale images. The original image is generally divided into several versions with various levels of information in a multiresolution image.

These are only a few examples; other sorts of images can also be combined using image fusion techniques, depending on the application's particular needs and objectives.

The method utilised in the image acquisition procedure is one of the drawbacks of poor spatial resolution imaging. This mechanism, which consists of a lens subsystem and optical sensors, may degrade as a result of out-of-focus and diffraction limits. The optical aberration or the turbulence in the atmosphere could also cause more distortions. The quality of the photograph also depends on the shutter speed and the distance between the camera and the subject. As a result of down sampling, the observed images are degraded and also feature aliasing. One can create a mathematical model that describes the image acquisition process in order to tackle the image reconstruction challenge. The forward or observation model connects the original image to the observed images.

In many different industries, including computer vision, remote sensing, medical imaging, surveillance, and more, image fusion techniques are frequently employed. There are multiple steps in the fusion process:

a. Image Alignment: Prior to fusion, the input images must be correctly aligned to guarantee that related features are spatially matched. If there are geometrical variations between the images, image registration techniques may be employed to precisely align them.
b. Image Decomposition: The input images are divided into many components or representations in many fusion algorithms. Wavelet transforms, Fourier transforms, and other multi-scale analytic approaches are frequently used decomposition techniques. Decomposition enables analysis and visual manipulation at several scales or frequency bands.
c. Fusion Rule: The information from the deconstructed images or image components is combined according to the fusion rule. There are various fusion methods, each with a unique fusion rule, such as pixel-level fusion, feature-level fusion, and decision-level fusion. The fusion rule may use more complicated algorithms based on predetermined criteria or mathematical operations such averaging, weighted blending, maximum or minimum selection.
d. Fusion Strategy: How the fusion rule is applied in various spatial or frequency bands is determined by the fusion strategy. It can entail employing several fusion rules in various regions or using

adaptive fusion techniques based on regional picture features. The goal of the fusion strategy is to streamline the fusion procedure for particular applications or desired results.

e. Post-processing: Following the fusion, additional enhancements or improvements to the fused image's visual quality may be made using post-processing techniques. These procedures may involve sharpening, contrast modification, noise reduction, or other picture enhancing methods.

The particular application requirements, the qualities of the incoming images, and the desired result all influence the choice of image fusion techniques and parameters. For various purposes or types of photos, different fusion techniques might be a better fit. Typically, measures like the preservation of significant details, greater visual quality, better feature representation, or improved performance in subsequent image analysis tasks are used to assess how effective image fusion is.

2. LITERATURE REVIEW

Riyahi et al. (2009) stated that the results produced by either the Brovey or Ehlers methods do a poorer job of preserving the spatial and spectral information of the objects in the original photos than PCA, which is why PCA fused images have the best spectral fidelity.Zhijun Wang et al. (2005) put forth a framework known as the GIF approach that maintains the ratios between the various bands, emphasises minute signature variations, and upholds the radiometric integrity of the data while enhancing spatial resolution. Shivsubramani Krishnamoorthy et al. (2010) stated and demonstrated that, DWT with Haar received a quality rating of 63.33 percent, which is significantly higher than the ratings provided to the other algorithms.

Shah S.K et al.(2014) concluded on the basis of their study that SWT was a superior image fusion technique than PCA and DWT. It also noted that spatial and transform domains were implementedand, Er.Kulvir Singh et al(2016) in another study,The quality of the fusion is typically influenced by the user's background, the fusion technique, and the data set being merged, the researcher found after looking at an image fusion survey

Nayera Nahvi et al. (2014) summarises the researcher's review of cutting-edge algorithms for picture fusion at the pixel and feature levels. Therefore, this review mentions the task-based fused picture assessment. The impact of contrast enhancement strategies on colour image segmentation was examined by the researcher. Bora,D et al. (2015) For both colour picture enhancement and colour image segmentation, it was discovered that HSV colour space performed better than LAB colour space even when there was noise present. It is concluded from the analysis of all experimental data that using HSV colour space for the task will improve the performance of the preprocessing method BSB-CLAHE for colour image segmentation. Vijayan,A et al. (2015)The Author presented many picture fusion techniques, including data-driven picture fusion among DWT, Laplacian, SVM, and HOSVD, as well as multi-scale picture fusion. Filter-based image fusion provides solutions for a variety of problems, including those involving multi-scale decomposition, colour distortion, the brightness of the fused output, etc. However, the guided filter has the drawback of taking longer to execute.Another efficient edge maintaining filter in computing is the local edge preserving filter (LEP). LEP offers superior photo filtration results compared to guided filter. By employing LEP filter for image fusion rather than guided filter for fusion, the guided filtering based fusion approach can be improved.The findings produced by the PCA approach, in contrast to those produced by either the Brovey or Ehlers approaches, better maintain the spectral and spatial information of the objects in the original photos, according to the researcher's visual inspection of the combined images. Kumar S. et al. (2009). The PCA fused picture has the best spectral fidelity, according to a statistical comparison of the PCA and the Brovey and Ehlers models. Consequently, it is the best technique among the three algorithms for QuickBird photo fusion.

G. Qu et al. (2002) based on interesting region recognition, this work developed a unique multiscale fusion method for the IR and VI image that can incorporate more background data and emphasise the interesting region with prominent items. With this approach, the guided filter and mean shift's benefits are combined. The NSCT domain then fuses the background areas. The high frequency layers are fused using an SF-PCNN-based approach, while the low frequency layers are fused using an improved weighted average technique based on per-pixel weighted average.According to experimental findings, the suggested fusion system performs better when subjected to unbiased evaluations and visual examination. In the study, a novel gradient-based photo fusion algorithm was proposed.Paul S et al. (2016) A wavelet-based gradient integration approach is utilised to obtain the fused luminance after the luminance channel is fused in the gradient domain. Based on a weighted sum of the chrominance channels in the input images, the chrominance channels are combined.Fast execution speed is a result of the effectiveness of the gradient reconstruction technique, which has a complexity of O(N). Studies show that the suggested algorithm produces excellent results for both multi-exposure and multi-focus images.

Singh, E et al. (2016) The author suggested a hybrid solution that addresses the issue of edge preservation and explicitly fused the images. Since Laplacian Pyramid is the second approach employed with wavelet fusion, it analyses every aspect of the image and aids in maintaining the standard of the fused image.The Laplacian Pyramid method simply monitors any change in the image's data by inspecting each pixel of the images. The proposed method has demonstrated superiority over the conventional methods in terms of edge preservation and is the highest calibre method.

Li, s et al. (2013) The researcher's review of cutting-edge methods for picture fusion at the pixel and feature levels is offered. Both stages of the fusion can be treated in either the transform domain or the spatial domain. Picture fusion algorithms that are implemented in a transform domain produce better results in many applications, especially those involving many modalities since they allow for the use of salient information that the human visual system is sensitive to. Among these transform methods, the DT-CWT seems to have the best performance because of its properties of good shift invariance and directional selectivity, while its complexity is not high. Numerous fusion rules have been introduced for general purpose or for specific applications. The maximum selection is the simplest and effective decision for most applications, but it is extremely sensitive to noise. An adaptive weighted average using statistical modelling, e.g. non-Gaussian is possibly the best fusion rule for the DT-CWT. It can be applied to various applications, such as visible/IR imaging, context enhancement, and medical imaging, both with noisy and noiseless pictures.

S Li et al. (2004) This study also presents two methods of fused picture assessment. Objective quality metrics, including Mutual Information, Petrovic and Xydeas Metric and Piella Metric, are utilized to assess the fused picture without the knowledge of groundtruth. As each picture fusion technique has been used in a variety of applications, their respective results should be assessed depending on the tasks for which they are used.

Diagnostic data for the patient has been generated by the wearable sensor and wirelessly sent to a smartphone using Bluetooth low energy technology.

Sharma P et al. (2018) A web interface receives information from the smartphone through Bluetooth/4G. The suggested system will be able to send out emergency alerts. In order to provide data that is as near to traditional systems as possible, sensors will be employed.

Liu J et al. (2023) In order to combine the features of image reconstruction decoding and create the fusion image, the saliency detection decoding is utilised as fusion weights. This efficiently extracts significant information from the source images and improves the fusion image's correspondence to visual perception. On a variety of publicly available datasets, experiments show that the proposed fusion approach provides state-of-the-art performance in infrared and visible picture fusion, multi-exposure image fusion, and medical image fusion.

Viyone G (2023) For students and professionals interested in learning more, this survey offers a thorough analysis of the literature. The fundamental components of the MS and HS image fusion are described, and three categories of related techniques (based on pansharpening, decomposition, and machine learning) are established.

Tang L et al. (2023) This study introduces a method for fusing infrared and visible images that doesn't require any darkness (DIVFusion), which effectively dispels shadows and makes it easier to gather complementing data. In particular, we first design a scene-illumination disentangled network (SIDNet) to remove illumination degradation in nighttime visible images while preserving informative features of source images in order to improve the fusion quality of nighttime images, which are hampered by low illumination, texture concealment, and colour distortion.

Ma J et al. (2022) In this paper, a brand-new generic image fusion framework called SwinFusion, based on cross-domain long-range learning and Swin Transformer, is proposed. In order to sufficiently integrate complementary information and cross-domain interaction, on the one hand, an attention-guided cross-domain module is developed. On the other hand, the issues with multi-scene picture fusion are generalised to a unified framework with appropriate intensity management, structure maintenance, and detail preservation. Extensive tests on both digital photography image fusion and multi-modal image fusion show how superior our SwinFusion is to both task-specific and cutting-edge unified image fusion algorithms.

3. AN APPROACH FOR IMAGE FUSION PROCESS: IMAGE FUSION TECHNIQUES

Spatial domain fusion and transform domain fusion are two basic categories into which image fusion techniques can be divided. Several well-known picture fusion techniques include:

- Pixel Level Image Fusion: The act of fusing numerous images at the pixel level to produce a single fused image is known as pixel-level image fusion. It is sometimes referred to as image blending or image combination. The goal of pixel-level fusion is to take the most important data from each input image and combine it to create a cohesive and appealing outcome.
- Feature Level Image fusion: The goal of feature-level image fusion, sometimes referred to as feature fusion or feature extraction-based fusion, is to merge pertinent features or representations taken from several input images to produce a fused image. The goal of feature-level fusion is to combine higher-level data or descriptors, as opposed to pixel-level fusion, which works directly on the pixel values.

- Decision Level Image fusion: Decision-level image fusion, sometimes referred to as decision fusion, concentrates on merging conclusions or results from several classifiers or algorithms that have been applied to input images. Decision-level fusion, as opposed to directly altering pixel values or features, tries to combine the judgements made by various algorithms or classifiers to produce a combined judgement or result.

In order to create a single, high-resolution image that is more informative than either of the original images, pixel level image fusion aims to integrate two dissimilar raw photos. The pixel level fusion methods include PCA (principal component analysis), Brovey, Wavelet, HIS, and others. The process of extracting characteristics from various photos and integrating them to create a single, more informative image is known as feature level image fusion. Ehlers' fusion and segment fusion are two examples of feature level techniques.Decision level image fusion is combining the results of different algorithms to provide the single decision. Decision level fusion methods are neural network such as convolutional neural network (CNN), Fuzzy logic etc.

3.1 Practical Implementation

In this research, the main emphasis is on principal component analysis (PCA) and convolutional neural network (CNN)as it is a comparative study of the two approaches of image fusion process. An uncorrelated linear combination of the original variable is created from a multivariate collection of correlated variables using principal component analysis (PCA).For images, it developsan uncorrelated feature space that can be used for further analysis. Advantage of using principal component analysis (PCA) is that the no. of bands are not restricted in this besides this there is also an disadvantage that it has blurring problems i.e. the results are not so clear result depends on the input image subset.

The simplicity, computational effectiveness, and capacity to capture the most important properties of the input images are just a few benefits of PCA image fusion. However, the dimensionality reduction procedure may result in information loss, particularly if the eliminated components contain crucial information.It is important to keep in mind that PCA image fusion is only one of many methods that are now available, and that its applicability will vary depending on the particular needs of the application and the features of the input images. In some situations, other fusion methods, including wavelet-based or deep learning-based fusion, might be preferable.

Figure 2. (a), (b) Input images (c) output Image of PCA

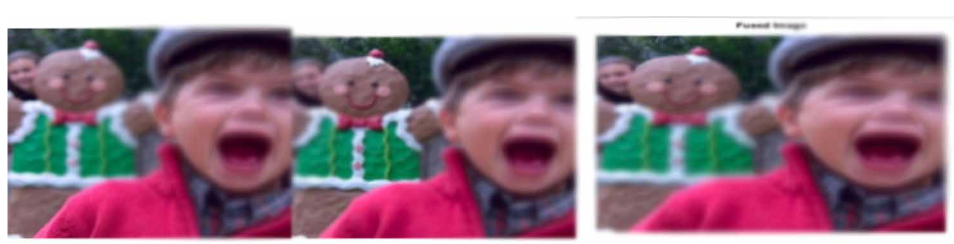
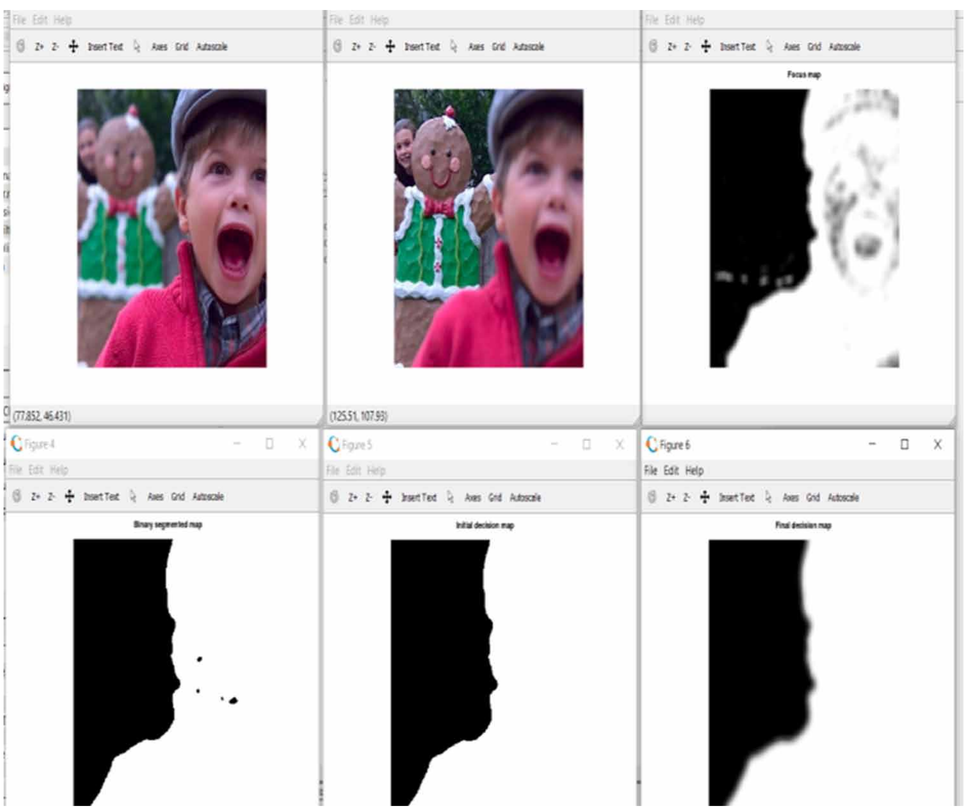


Figure 3. (a),(b) Input image (c) output image of CNN

Figure 4. Other output images of CNN



CNN (Convolutional Neural Network)have freshly been used for multi-focus image fusion. CNN takes input and process and categorize it using various layers (having filters) in the convolutional neural network. To classify an object with probabilistic values, these layers—CONVULUTIONAL LAYER, POOLING LAYER, and FULLY CONNECTED LAYER—apply the softmax function (0 and 1).Advantage of using CNN (convolutional neural network) is that it has the highest accuracy in image recognition system along with the advantage it also has disadvantage that it takes lot of time in execution and possesses high computational cost.

CNN image fusion has a number of benefits, including the capacity to capture complicated correlations and patterns and the ability to automatically learn and extract relevant features from the input images. However, training a CNN can be computationally demanding and necessitates a sizable labelled dataset. The richness and diversity of the training dataset, the design and performance of the CNN architecture, and other factors all have a significant impact on how effectively CNN image fusion works. To get the best fusion results for a given application, experimentation and fine-tuning of the network parameters are frequently necessary.

Some more output pictures are there in CNN that are:

The image is first subjected to fusion scanning. The focus map is first built using focus-based measurements, which are computed using sections of erratic form that have been refined or divided in response to changing image contents. Segmentation is used to build an area map after the initial production of an all-focus image. Then, by examining each region's spatial-focal property, it is determined whether each region has to be iteratively divided into sub-regions. The final region map is used to perform regionally best focusing after iterative splitting, which selects the best focused pixels from the image stack.The label image may easily be transformed into a depth image since each pixel's label in the resulting label picture acts as the image index from which the pixel with the best focus is chosen. The best focus will be chosen for regions with unknown focus profiles using spatial propagation from nearby confident areas.

MSE: MSE is mean square error that is the comparison parameter to determine the quality of image. It represents the aggregate squared error between the two images. MSE plays a vital role in the calculation of PSNR value. MSE value is directly proportional to the error presents in the image. The less is the MSE the less is the error. Lower MSE value represents the high-quality image.

Formula to calculate MSE is:

$$MSE = \Sigma M,N\, [I1\,(m,n) - I2\,(m,n)]\, 2 \,/\, (M*N)$$

Here in the equation: M and N are the number of rows and columns in the source images.

1. PSNR: It is used to calculate accuracy of the model which is used to compute the peak SNR between two images; it is also calculated in decibels. Quality of final image is directly proportional to the PSNR value, if the PSNR value is high, the quality of final image also hikes or vice versa. To calculate the PSNR value, first have to calculate MSE.

PSNR is then calculated by:

$$PSNR=10log10(R2MSE)$$

Here, R is the highest deviation in the source image.

Table 1. Analysis of PCA and CNN

S.N	Attribute	PCA	CNN
1	Input Image	  	  
2	Output Image	  	  
3	Execution Time	0.40803 seconds	191.397 seconds
4	Accuracy	Less Accurate than CNN	More Accurate than PCA
5	Cost	Less computational cost.	More computational cost.
6	Approach	Feature Extraction	End-To-End Approach
7	Clarity	Less clear	More clear
8	MSE	65.4080	67.7141
9	PSNR	17.6171	17.6241

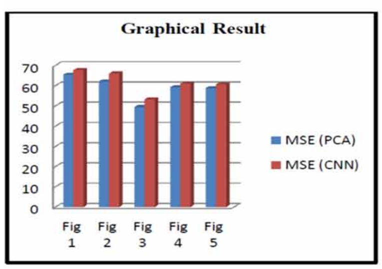
4. COMAPARATIVE STUDY TABLE: PCA VS CNN

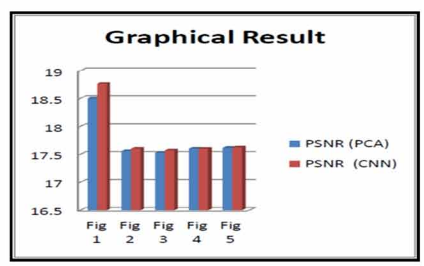
Table I above shows the comparative analysis of PCA and CNN image fusion methods. This analysis was performed as follows:

1. The input images are first taken into model to fuse informative segments.
2. Output images then analyzed with PCA and CNN models.
3. Execution Time: PCA is a basic algorithm, that takes less time to compute and providing results whereas CNN is such a complex model that takes comparatively more time.
4. Approach is different in both of the models. In PCA, it is Feature extraction and in CNN, it is end-to-end.
5. Cost Analysis: Cost of PCA is comparatively less than that of CNN due to simpler model architecture.
6. Accuracy of the models is then calculated on 3 main features; Visual interpretation. MSE and PSNR. Visually the output image of CNN is much clear than PCA image fusion method. Accuracy of MSE is measured with the inverse relation of value, lower is the MSE, higher is the accuracy. PSNR shows the positive relation with the accuracy, higher the PSNR, higher is the accuracy. Hence, from the table most of the parameter calculation indicates that the CNN is better than PCA in terms of clarity and quality but PCA is better in terms of simplicity and execution time.

Graphical Results of Implementation

Figure 5. a) Graphical result MSE b) Graphical result PSNR





Graphs above shows the MSE and PSNR results for PCA and CNN on five image datasets. All the images were tested on MATLAB for these two models of image fusion.

5. CONCLUSION AND FUTURE SCOPE OF STUDY

Input images were fused to integrate relevant information from multiple images to one image using PCA and CNN image fusion methods. Results were analyzed by using various parameters listed in table 1 above. On the basis of comparison between Principal Component Analysis (PCA) and Convolutional Neural Network (CNN)from the table that were concluded by the experimentation performed on MAT-

LAB platform. The researcher revealed that CNN is much favorable in terms of image quality and clarity but less favorable in terms of time and cost. The researcher found that the PCA produces blurry output image while CNN generated more clear output image. MSE and PSNR values also concludes the good accuracy of CNN model. The researcher recommended that the future scope of this study is not limited to comparison between two approaches, the study should be extended in terms of improvement in the quality of PCA generated output by using some standard algorithm for reducing the noise in the image and CNN should also be processed by using some minimization or optimization algorithm to minimize the running time and cost of the fusion process.

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