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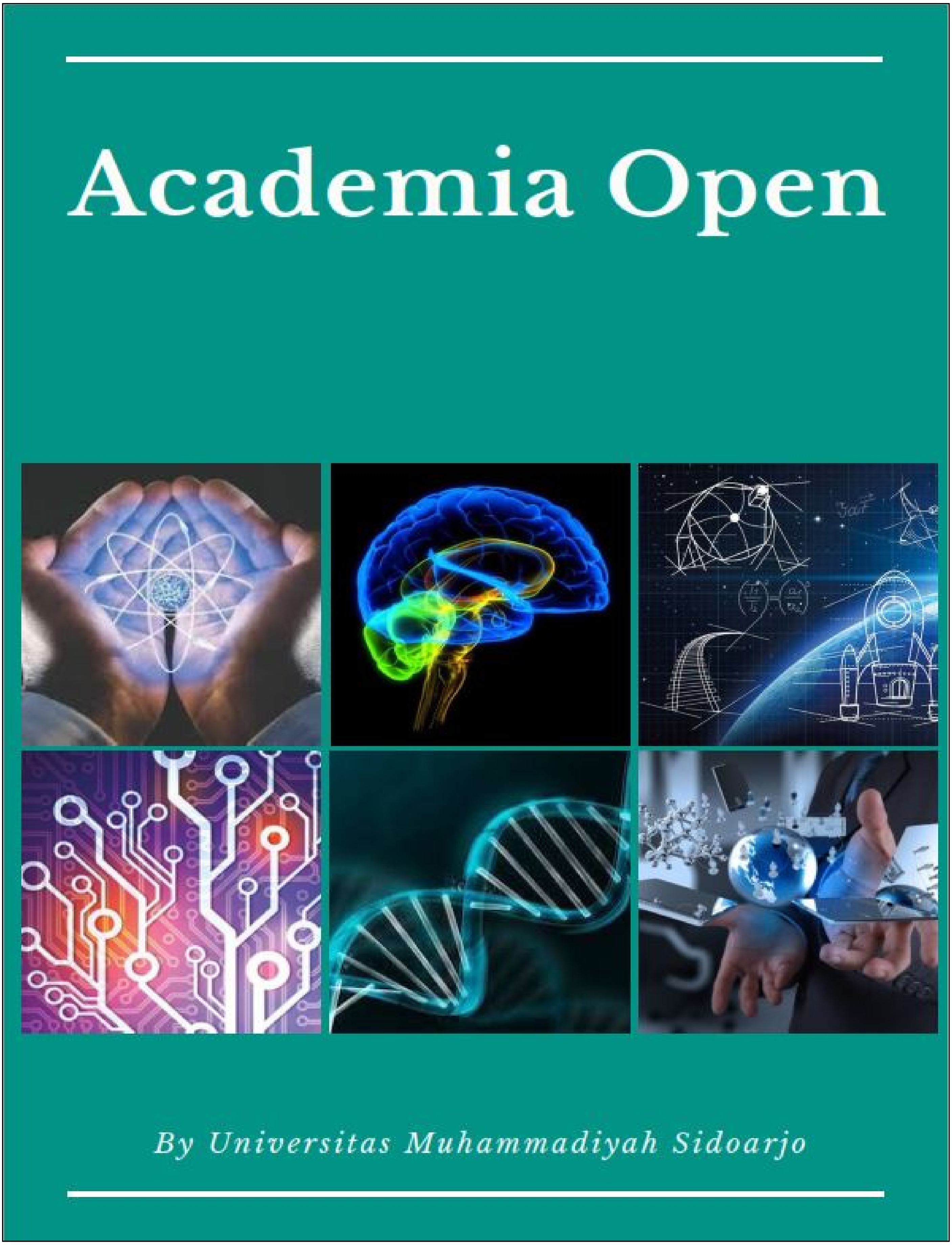

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Comparison of Independent and Principal Component Analysis in Bighorn Basin Imagery

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Abstract

General Background: Dimensionality reduction is a critical technique in image processing, especially for multispectral satellite imagery where data redundancy and computational complexity are prevalent challenges. **Specific Background:** Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are two widely adopted methods for reducing dimensionality while preserving essential image information. **Knowledge Gap:** Despite their extensive usage, comparative assessments of their performance in multispectral image reconstruction, particularly in geospatial contexts, remain limited. **Aims:** This study aims to evaluate and compare the effectiveness of PCA and ICA in processing Landsat multispectral images of the Bighorn Basin by assessing image reconstruction fidelity. **Results:** The findings reveal that PCA outperforms ICA in reconstruction quality, achieving higher Peak Signal-to-Noise Ratio (PSNR) values (up to 27.78 dB) and lower Root Mean Square Error (RMSE), whereas ICA, though proficient in extracting statistically independent features, demonstrated lower fidelity (PSNR = 17.63 dB). **Novelty:** The work offers a rigorous, side-by-side quantitative analysis of PCA and ICA applied to real-world satellite data, highlighting variance behavior and reconstruction trade-offs. **Implications:** These insights inform the selection of dimensionality reduction techniques in remote sensing tasks—PCA for optimal reconstruction and noise elimination, and ICA for feature extraction based on statistical independence.

Highlights:

- PCA provides superior image reconstruction accuracy with higher PSNR and lower RMSE.
- ICA excels in isolating statistically independent features for advanced analysis.
- PCA components show faster variance decay, making them efficient for compression.

Keywords: Dimensionality Reduction, Satellite Imagery, Principal Component Analysis, Independent Component Analysis, Image Reconstruction

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Introduction

Image processing plays a crucial role in modern scientific and industrial applications, particularly in the field of remote sensing, medical imaging, and computer vision. One of the most significant challenges in handling high-dimensional image data is the computational complexity and storage requirements associated with large multi-band images, such as multispectral images[1].

The best way to solve such problems is to use dimensionality techniques in order to transpose the high-dimensional data of images to a lower-dimensional space in order to maintain the crucial data. The most common statistical methods to perform that are Principal Component Analysis (PCA) and Independent Component Analysis (ICA). PCA tries to maximize variance distinct orthogonal factors, thus trying to describe the most striking data patterns, and ICA tries to separate statistically independent source signals and observed data [2].

In this study, dimensionality reduction was performed using both PCA and ICA on a satellite image. The resulting reduced components were used to reconstruct the original image bands, and the quality of reconstruction was evaluated using error metrics, particularly the Peak Signal-to-Noise Ratio (PSNR) and Root Mean Squared Error (RMSE). These metrics provide quantitative assessments of the fidelity of the reconstructed images, which is crucial for validating the effectiveness of the dimensionality reduction technique[3].

1. Digital Image

The digital image f(x,y) is given as a 2-dimensional grid of data such that at each pixel the value indicates the brightness of the image at the point of (x,y). The least complex image is the monochrome (one color, what we are conventionally used to call black and white) example of the image data, and all others kinds of the image data are more complex and they need to be expanded or adapted to this model, usually there are multi-band images (color, multispectral) and they can be modeled according to functions f(x,y) representing separate bands of brightness data. The images could be categorized as the following ones [4]**:**

2. Multispectral Image

To obtain the information of the earth, a process of remote sensing is employed. It involves the detection of, or collection of information of a target by a sensor that is an arm-length away. This data is coded in form of Multispectral images (i.e. they are not observed through the wavelengths sensed directly by the human system); the code is not image in the ordinary meaning of this word as a part of information is not visible at all and might be sensed only by some specialized device [5].

3. Statistical view points

The entire subject of statistics is based on the idea that how the big set of data can be analyzed, in terms of the relationships between the individual points in that data set. Therefore, the following subsections would be helpful to illustrate the PC analysis.

a. Standard Deviation

In probability and statistics, the standard deviation of a probability distribution, random variable or a whole population of values is defined as the square root of the variance. In the case of a whole population of values the standard deviation can be interpreted as the root mean square (RMS) deviation of the values from their arithmetic mean. Standard deviation can also be defined for samples as an estimate of the standard deviation of the whole population, but there are at least two different common definitions for it. The standard deviation is always non-negative, representing the most common measure of statistical dispersion, measuring how spread out the values in a data set are [6]. The standard deviation has no maximum value although it is limited for most data sets

b. Variance

In probability theory and statistics, The variance is a term used to measure of how far a set of numbers are spread out from each other. how far the numbers lie from the mean (expected value) [7]. As its name implies it gives in a standard form an indication of the possible deviations from the mean. The variance of

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a real-valued random variable is its second central moment, and it also happens to be its second cumulant. If $\mu = E(X)$ is the expected value (mean) of the random variable X, then the variance is

$$\mathrm{var}(X) = E((X-\mu)^2) \qquad (1)$$

In plain language, it can be expressed as "The average of the square of the distance of each data point from the mean". Many distributions, such as the Cauchy distribution, do not have a variance because of the relevant integral diverges. In particular, if a distribution does not have an expected value, it does not have a variance either. The converse is not true: there are distributions for which the expected value exists, but the variance does not [8].

c. Covariance matrix

The covariance matrix is a 2-dimensional table of variances between the components in a vector that is used in statistics and probability theory. It is the conceptual generalization to higher dimensions, of the notion of the variance of a random variable taking values in the real numbers. In case X is an n-dimensional column vector with its scalar random variable components, and E(Xk) = mu k is the expected value of the kth element of X, or μk = E(Xk) then the covariance matrix is defined as [9] **:**

$$\sum = E\left[(X - E[X])(X - E[X])^T \right] \qquad (2)$$

$$= \begin{bmatrix} \mathrm{E}[(X_1-\mu_1)(X_1-\mu_1)] & \mathrm{E}[(X_1-\mu_1)(X_2-\mu_2)] & \cdots & \mathrm{E}[(X_1-\mu_1)(X_n-\mu_n)] \\ \mathrm{E}[(X_2-\mu_2)(X_1-\mu_1)] & \mathrm{E}[(X_2-\mu_2)(X_2-\mu_2)] & \cdots & \mathrm{E}[(X_2-\mu_2)(X_n-\mu_n)] \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{E}[(X_n-\mu_n)(X_1-\mu_1)] & \mathrm{E}[(X_n-\mu_n)(X_2-\mu_2)] & \cdots & \mathrm{E}[(X_n-\mu_n)(X_n-\mu_n)] \end{bmatrix}$$

The (i, j) element is the covariance between X_i and X_j

This matrix is termed the variance of the random vector X, since it serves as a natural extension of the one-dimensional notion of variance. It is referred to as the covariance matrix, since it represents the matrix of variances of the standard components of X. Regrettably, several ideologies exhibit inherent conflicts with one another:

Standard notation:

$$\mathrm{var}(X) = E\left[(X - E[X])(X - E[X])^T \right] \qquad (3)$$

Also standard notation (unfortunately conflicting with the above):

$$\mathrm{cov}(X) = E\left[(X - E[X])(X - E[X])^T \right] \qquad (4)$$

Also standard notation:

$$\mathrm{cov}(X,Y) = E\left[(X - E[X])(Y - E[Y])^T \right] \qquad (5)$$

(the **"cross-covariance"** between two random vectors)

The first two of these usages conflict with each other. The first and third are in perfect harmony [6].

This covariance matrix (quite simple though) is a very helpful tool in many very different spheres. Based on it, one can obtain a transformation matrix that will make it possible to fully decorrelate the data or, in another perspective, to compute a good basis according to which the data can be represented in a compact form. It is referred to as principal components analysis (PCA).

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d. Eigenvectors and Eigenvalues

A multiplying of two matrices together, provided they are compatible sizes. Eigenvectors are a special case of this. Consider the two multiplications between a matrix and a vector. If $A\mathbf{u} = r\mathbf{u}$ for some nonzero vector $\mathbf{u}$ and some number r, then we say that r is an eigenvalue of the matrix A, and $\mathbf{u}$ is an eigenvector of A for that eigenvalue [11].

4. Error Metrics: PSNR and RMSE

a. Peak Signal-to-Noise Ratio (PSNR)

Peak Signal-to-Noise Ratio (PSNR) is a widely used metric for assessing the quality of reconstructed or compressed images compared to their original versions. It is expressed in decibels (dB) and is derived from the Mean Squared Error (MSE). Higher PSNR values generally indicate better reconstruction quality[12].The PSNR is defined as:

PSNR = 10 * log10((MAX ^2) / MSE) (6)

Where:
- MAX is the maximum possible pixel value of the image.
- MSE is the Mean Squared Error between the original and reconstructed images.

b. Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is another commonly used metric for measuring the difference between values predicted by a model or system and the actual values observed. In the context of image comparison, it measures the average magnitude of the error between the original and the reconstructed images. Lower RMSE values indicate better accuracy.The RMSE is defined as[13]: RMSE = sqrt(MSE) (7)
Where MSE is the mean squared difference between original and reconstructed pixel values.

5. Image Transformation

The Digital Image Processing provides unlimited variety of possible transformations that could be applied to remotely sensed information. Two are cited here, namely, due to their unique importance in the applications with regard to environmental monitoring [14]. Semiblind methods, Principal Component Analysis (PCA) and Independent Component Analysis (ICA).

a. Principal Component Analysis (PCA)

Principal Component Analysis has become a very common application in image processing particularly in image compression. It is also known as the Karhunen-Leove transform also as Karhunen-Leove transform KLT or Hotelling transform. Principal components analysis PCA is a statistical operation which enables one to identify fewer dimensions that explain the greatest possible degree of variance in the data matrix. The eigenvector of the input data covariance matrix are the PCA basis vectors.[15].

The PCA dimensional reduction is based on a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components PCs [16].

b. Independent Component Analysis (ICA)

For the observed multivariate data, which is usually provided as a sizable database of samples, ICA defines a generative model. The mixing system is likewise unknown, and it is assumed that the data variables in the model are either linear or nonlinear blends of some unknown latent variables. The latent variables, also known as the independent component (IC) of the observed data, are considered to be non-Gaussian and mutually independent. These independent elements are sometimes referred to as sources or ICA-findable factors [17].ICA severs from two ambiguities, there are:

1.The variances (energies) of the independent components cannot be determined.

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2.The order of the independent components cannot be determined.

There are mainly two distinct approaches towards computing the ICA, off-line (batch) processing, and on-line algorithms. The Independent Component Analysis (ICA) approach for movement estimation includes (i) initial training of movement data based on the known dislocations of the object with different noise levels, (ii) and the estimation of unknown new object dislocations.

Independent Component Analysis (ICA) is a complex-valued algorithm that does latent variable extraction of sets of measurements or signals. ICA also is based on the statistical model, according to which actual multivariate data (usually presented as a huge collection of samples) are considered to be nonlinear (or linear) mixture of some unknown latent variables. Mixing coefficients remain unknown also. The latent variables are nongaussian and jointly independent and they will be referred to as the independent components of the observed data. These sources, or factors are also known as independent components which can be identified by ICA. Therefore we can interpret ICA as a running off the Principal Component Analysis and Factor Analysis. ICA is a richer method, though, that can detect the sources, when these classical approaches will fail utterly[18].

6. Objective of the Study

The primary objective of this study is to investigate and compare the effectiveness of two widely used dimensionality reduction techniques(Principal Component Analysis (PCA) and Independent Component Analysis (ICA)) in the context of satellite image processing. The study aims to:

a. Apply PCA and ICA to a multispectral satellite image to reduce its dimensionality while preserving essential spatial and spectral information.

b. Reconstruct the original image bands from the reduced components obtained by each method.

c. Quantitatively evaluate the reconstruction performance using error metrics such as Peak Signal-to-Noise Ratio (PSNR), Root Mean Square Error (RMSE), and Structural Similarity Index (SSIM).

d. Compare the results from both PCA and ICA to assess which method provides better preservation of image quality during dimensionality reduction.

e. Analyze variance contribution and interpret the significance of the first few components in representing the original image data.

This comparative analysis aims to provide valuable insights for researchers and practitioners in selecting the appropriate technique for efficient and accurate processing of high-dimensional satellite imagery.

Method

A. Data

This study utilizes a multispectral satellite image of the Bighorn Basin, located in northwestern Wyoming, USA as region of significant geological and environmental importance. The image was acquired from Landsat TM data and consists of six spectral bands covering the wavelength range from 0.485 to 2.215 micrometers, stored in Band Sequential (BSQ) format with an ENVI Standard file structure as shown in figure (1). The spatial resolution of the image is 512 × 512 pixels, with a 30-meter pixel size. According to the metadata, the image is geometrically corrected, projected to the UTM coordinate system, Zone 13 North, using the North America 1927 (NAD27) geodetic datum. Radiometric metadata indicates that the image has been calibrated to reflectance, making it suitable for spectral analysis without the need for further radiometric correction. Therefore, this dataset is well-suited for evaluating dimensionality reduction techniques such as PCA and ICA.

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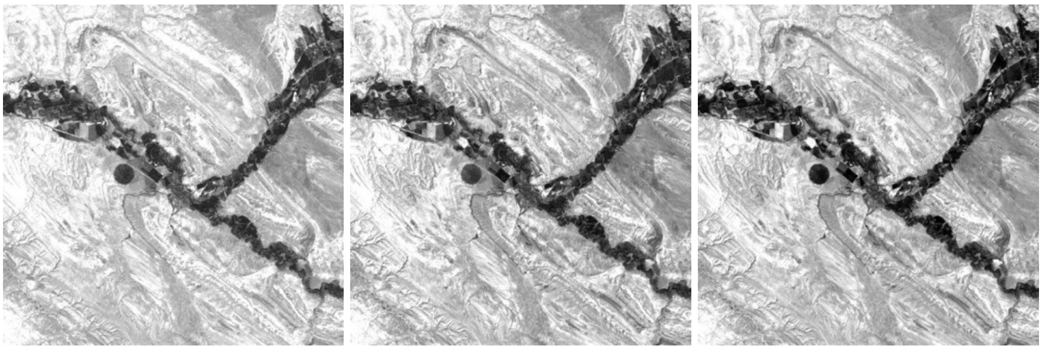
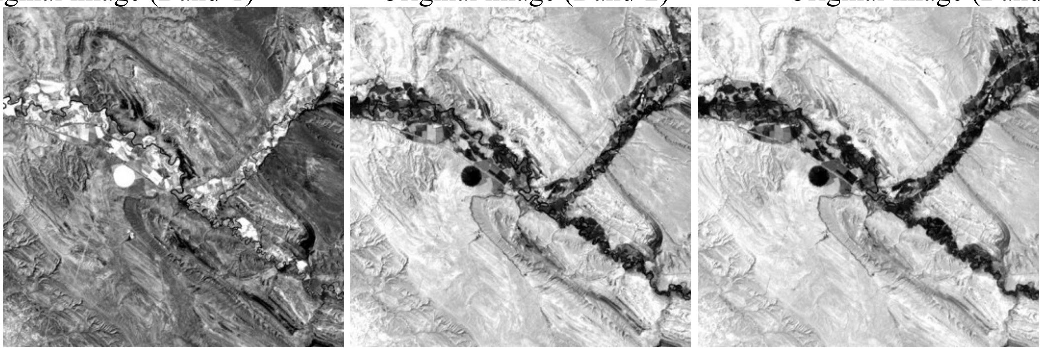


Original image (Band-1) Original image (Band-2) Original image (Band-3)



Original image (Band-4) Original image (Band-5) Original image (Band-7)

Figure 1. Represent samples of six visible bands of multi-spectral images, representing Bighom basin, Landsat TM, 28.5 meter, from ENVI database.

B. Preprocessing and Data Validation

Prior to applying dimensionality reduction techniques, the satellite image underwent essential preprocessing to ensure data integrity and spectral consistency. Initially, missing or invalid pixel values were identified using the compute Statistics tool in ENVI 4.7. Visual inspection and statistical summaries revealed whether extreme values (e.g., -9999 or 0) existed, which commonly indicate non-informative or missing data. Where necessary, these values were excluded from further analysis by assigning them as a data ignore value in the image header. To ensure spectral consistency, each band was inspected to verify that all shared identical spatial dimensions, data type, and pixel size. The metadata viewer was used to confirm uniformity in projection, wavelength alignment, and interleave format. Additionally, the Spectral Profile Viewer tool was employed to verify the spectral coherence of randomly selected pixels across all bands. This preprocessing step guaranteed that the input data was clean, consistent, and suitable for reliable application of PCA and ICA techniques.

C. Methodology

This study aims to perform a quantitative and qualitative comparison between two widely used dimensionality reduction techniques:

1. Principal Component Analysis (PCA)
2. Independent Component Analysis (ICA)

Both methods were applied to the same dataset (the pre-processed satellite image), following the steps below:

1. Initial preprocessing to ensure the image is free of missing values and the spectral bands are consistent.
2. Application of PCA**,** extracting the principal components ranked by the amount of explained variance.

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3. Application of ICA using the FastICA algorithm to extract statistically independent components with non-Gaussian distributions.
4. Image reconstruction after dimensionality reduction using both techniques to assess recovery quality.
5. Quantitative comparison of the output using objective metrics, including:
    a. Peak Signal-to-Noise Ratio (PSNR)
    b. Root Mean Square Error (RMSE)

Results and Discussion

A. Principal Component Analysis Implementation in ENVI 4.7

One method that can be applied in simplification of a dataset is the principal components analysis (PCA). It is a linear transformation that selects a new coordinate system on the data set so that the largest variance of any projection of the data set will fall on the first axis (say, termed the first principal component), whose second largest variance will fall on the second axis, and so on.

PCA can be employed as dimensionality reduction method in a dataset, which involves retaining only those factors of the dataset which are capable of contributing maximum to its variance by retaining the lower order principal components and discounting higher order ones. The concept here is that; The low-order elements usually bring with them the most vital elements of the data. Nonetheless, the same analysis can be applied conveniently to various multivariate responses. The main role of the analysis is to specify the member of family of response vectors with the help of a small set of parameters. The parameters are the scalar multiples of basic response vector that can be combined to form a linear combination that can be used to restore the experimentally observed difference between the response functions.

The capability to fit the intricate response function with a few parameters makes the search of connection between the observed change in response to the causal variables of the experiment.

One such value of the analysis is that characteristic vectors computed using a family of response vectors could be in a position to synthesize response vectors which were not represented in the initial family and hence a succinct state of the fresh data would be produced. When there exists new data that is not even fitted by the established vectors, then this implies that the new data belong to a fundamentally different population of response variability as was the case with the variability of the initial family of responses. It should be mentioned that characteristic vector analysis represents the empirical procedure. Figure (2) indicates that three principal components images, We observe that the first principal (PC1) have lot of information power (high) as compared to other principals, this is because it has the largest eigenvalue. Table (1) indicates that the three components can be used to reduce the dimensionality of the dataset indicating that no large portion of the spectral information is compromised in the reduction of dimensionality of the dataset across six bands. The table (2) shows the values of PSNR and RMSE as a result of the comparison between the original three spectral bands of the multispectral image and the corresponding bands with the same indices but retrieved with the help of inverse PCA and first three principal components.The better is the reconstruction quality, the higher the PSNR and the lower the RMSE are. Band 3 had a fidelity and PSNR of the highest value 27.78 dB with the RMSE that was the lowest of about 193.69. It implies that the third one retained most of the sensor information in the original image probably because it contributed greatly to the overall variance that was elicited during PCA transformation .All calculations were carried out in Python program through package Core .Figure (3) illustrates the original multi-spectral bands and the Reconstructed image using only three first PCs.

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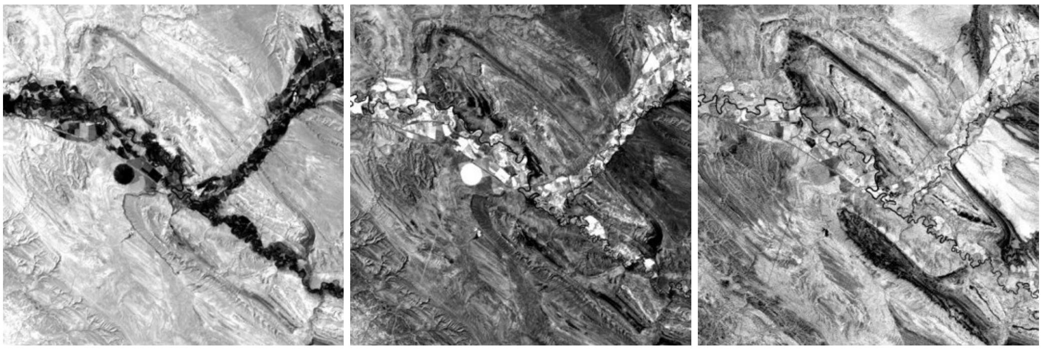
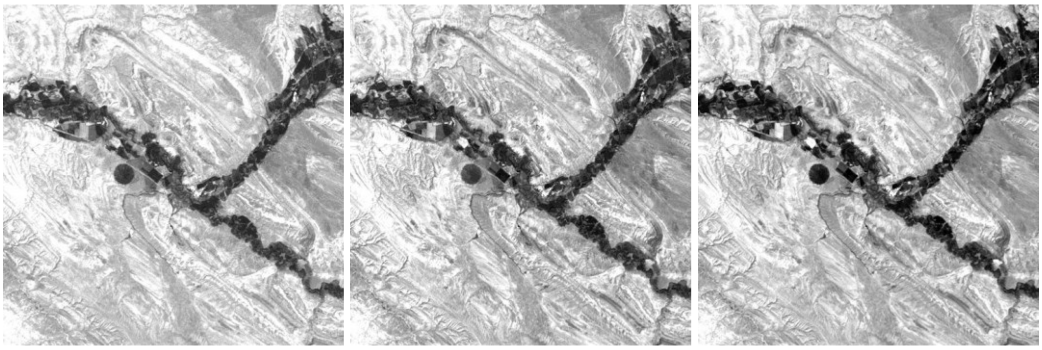
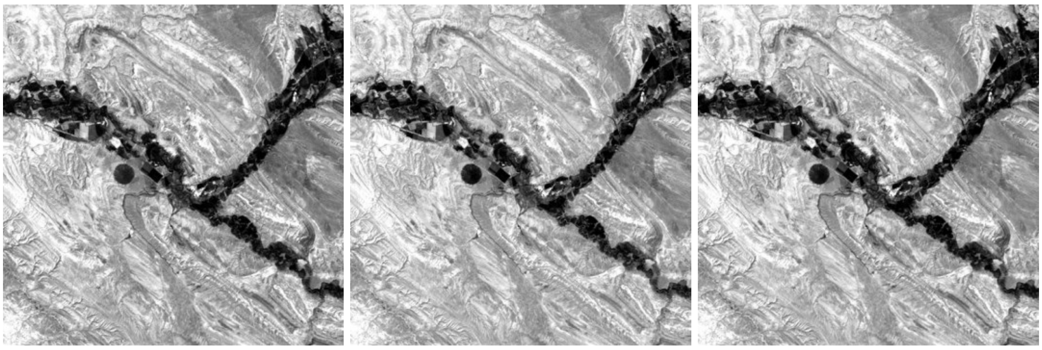


1st PCA image 2nd PCA image 3rd PCA image

Figure 2. Represents the Three PCs of the processed image



Original image (Band-1) Original image (Band-2) Original image (Band-3)



Reconstructed image (Band-1) Reconstructed image (Band-2) Reconstructed image (Band-3)

Figure 3. The original multi-spectral bands and the Reconstructed image using only the three first PCs.

PC (Band)	Eigenvalue	percentage of variance
PC1	127.037732	80.45%
PC2	22.992189	14.57%
PC3	6.009075	3.81%
PC4	1.085246	0.69%
PC5	0.573050	0.36%
PC6	0.206078	0.13%

Table 1. Eigenvalues and Percentage of Variance for the First Three Principal Components from PCA of the Bighorn Basin Image

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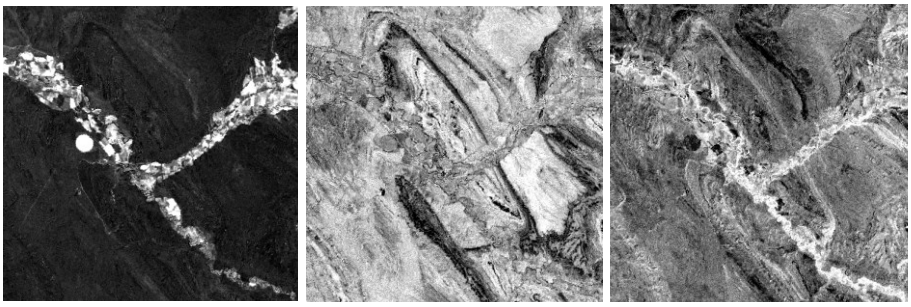
Band	PSNR (dB)	RMSE
Band 1	24.87	277.46
Band 2	25.13	269.09
Band 3	27.78	193.69

Table 2. PSNR and RMSE between Original Bands and Their Inverse PCA Reconstructions

B. Independent Component Analysis (ICA) Implementation in Python program

The application of Independent Component Analysis (ICA) on the multispectral satellite imagery yielded three statistically independent components, each aiming to maximize the non-Gaussianity of the observed signals. Unlike PCA, which decorrelates the data based on variance, ICA focuses on separating mixed signals into independent sources, thereby revealing hidden structures that are not necessarily aligned with the direction of maximum variance. Table (3) presents the variance contribution of the first three Independent Component Analysis (ICA) components, derived from their corresponding eigenvalues. The results indicate that the first ICA component accounts for approximately 80.01% of the total variance, suggesting it captures the majority of the statistically independent information within the dataset. The second and third components contribute 14.48% and 3.78%**,** respectively. This distribution implies that while the first component is dominant in terms of information content, the subsequent components offer marginal contributions. Such a sharp decline in variance contribution reflects the effectiveness of ICA in concentrating independent features into the first few components, which can be particularly beneficial for dimensionality reduction and feature extraction in remote sensing .Figure (4) show the first three independent components obtained from the Independent Component Analysis (ICA) applied to the satellite image. These components represent statistically independent features within the dataset, where IC_1 captures the most dominant independent structure, followed by IC_2 and IC_3 with gradually decreasing contributions. The visual patterns observed in the components highlight distinct geospatial variations, potentially corresponding to different land cover types or geological formations. .Figure (5) shows the original multi-spectral bands and the Reconstructed image using only the three first ICs. Table (4) presents a quantitative evaluation of the fidelity between the original multispectral bands and their corresponding reconstructed components obtained via inverse Independent Component Analysis (ICA). The PSNR values range from 16.82 dB to 20.02 dB, indicating moderate to fair reconstruction quality. The Root Mean Square Error (RMSE) results, derived from the PSNR values, range between 255.35 and 367.51, with Band 1 showing the lowest RMSE (highest fidelity) and Band 2 the highest RMSE (lowest fidelity). These findings suggest that the first ICA component preserves more of the original spectral information compared to subsequent components. The declining accuracy in reconstruction for higher-order components reflects the reduced variance captured by these components, consistent with ICA's prioritization of statistical independence over energy compaction.



1st ICA image 2nd ICA image 3rd ICA image

Figure 4. Represents the Three ICs of the processed image

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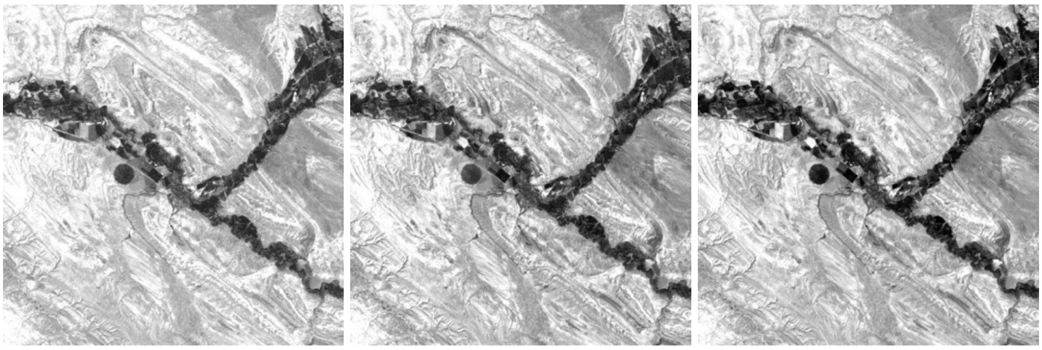
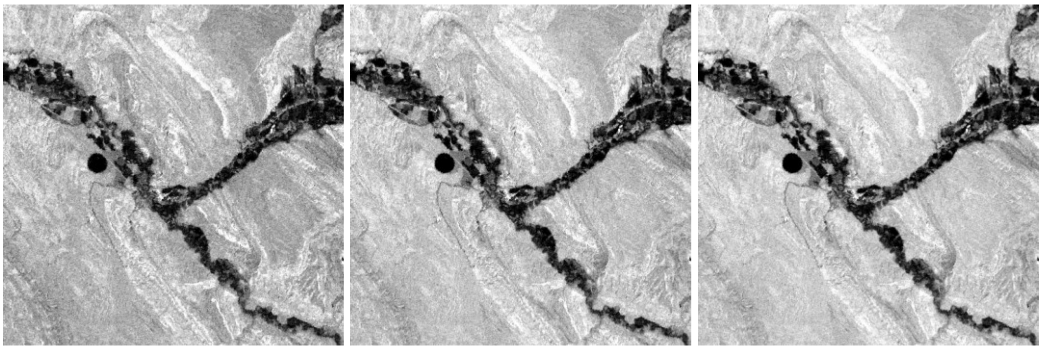


Original image (Band-1) Original image (Band-2) Original image (Band-3)



Reconstructed image (Band-1) Reconstructed image (Band-2) Reconstructed image (Band-3)

Figure 5. The original multi-spectral bands and the Reconstructed image using only the three first ICs.

ICA Component	Eigenvalue	Variance Contribution (%)
ICA1	127.04	80.01%
ICA2	22.99	14.48%
ICA3	6.01	3.78%

Table 3. Variance Contribution of the First Three ICA Components Based on Eigenvalues

Band	PSNR (dB)	RMSE
Band 1 vs Reconstructed image	20.02	255.35
Band 2 vs Reconstructed image	16.82	367.51
Band 3 vs Reconstructed image	17.63	333.03

Table 4. Quantitative Evaluation of Reconstruction Accuracy between Original Bands and Reconstructed Image Using PSNR and RMSE

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Conclusion

This study has examined and compared the performance of two prominent dimensionality reduction techniques, Principal Component Analysis (PCA) and Independent Component Analysis (ICA), in the context of multispectral image processing. By evaluating the reconstructed image components against their corresponding original spectral bands using objective image quality metrics namely PSNR, RMSE ,we observed that both PCA and ICA effectively reduce data dimensionality while preserving significant image information.

However, the quantitative results indicate that PCA generally achieves better reconstruction quality, especially in terms of lower RMSE and higher PSNR value. ICA, on the other hand, demonstrates its strength in separating statistically independent components, although its performance in reconstructing original spatial-spectral structures is slightly lower.These findings suggest that PCA may be more suitable when the primary objective is optimal image reconstruction and minimal loss, while ICA could be advantageous for tasks focused on feature extraction or source separation. Overall, the study contributes to a deeper understanding of the trade-offs between PCA and ICA in remote sensing and multispectral image analysis, offering insights for selecting the most appropriate technique based on specific application requirements.

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