

Design Assessment and Simulation of PCA Based Image Difference Detection and Segmentation for Satellite Images Using Machine Learning

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Abstract

It is possible to define the quantity of temporal effects by employing multitemporal data sets to discover changes in nature or in the status of any object based on observations taken at various points in time. It's not uncommon to come across a variety of different methods for spotting changes in data. These methods can be categorized under a single umbrella term. There are two primary areas of study: supervised and unsupervised change detection. In this study, the goal is to identify the changes in land cover. Covers a specific area in Kayseri using unsupervised change detection algorithms and Landsat satellite pictures from various years have been gleaned through the use of remote sensing. In the meantime, image differencing is taking place. The method will be applied to the photographs using the image-enhancing process. In the next step, Principal Component Analysis (PCA) is employed. The difference image will be analyzed using Component Analysis. To find out which locations have and which do not. As a first step, a procedure must be in place. We've finished registering images one after the other. Consequently, the photos are being linked together. After then, it's back to black and white. Three non-overlapping portions of the difference image have been created. This can be done using the principal component analysis method. From the eigenvector space, we may get to the fundamental components. As a last point, the major feature vector space fuzzy C-Means Clustering is used to divide the component into two clusters, and then a change detection technique is carried out. As the world's population grew, farmland expansion and unplanned land encroachment intensified, resulting in uncontrolled deforestation around the globe. This project uses unsupervised learning algorithm K-means clustering. In a cost-effective manner that can be employed by officials, companies as well as private groups, to assist in fighting illicit deforestation and analysis of satellite database.

Keywords: Supervised Learning, Unsupervised Learning, MSE, PSNR, Satellite Images.

1. INTRODUCTION

Digital image processing processes the manipulation of digital images through a digital computer. DIP is a subfield of signals and structures, but focuses on pictures. It focuses on creating an image-processing computer system. The input of the system is a numerical image and the system process, using successful image algorithms and providing an image as an output. The best-known example is Adobe Image Shop. This is one

of the most common applications for digital image treatment. In Fig. 1.1, an image was collected by a camera and sent to a digital system to collect all the other details and focus only on the water drop by zooming in so that the image quality stays equal.

Processing the digital image involves various methods including data formatting, data correction, digital enhancement for better visual interpretation and automation by computer. In this respect, the digital data

is stored like a computer hard drive on memory storage. Computer system, also known as an image analysis system, also includes appropriate data processing software and hardware, is another requirement for

digital image processing. Thus, the processing of images is a type of processing of information in which both input and output are pictures such as frames or plot diagrams.

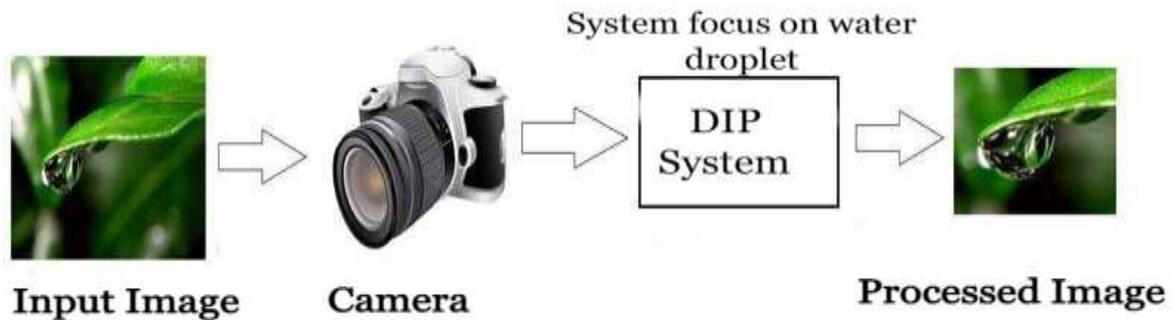


Figure 1.1 Example Digital Image Processing System

In most image processing techniques, images are treated as two-dimensional signals. Image is defined as the function of two-dimensional light intensities $f(x, y)$ where x and y represent the spatial coordinates. F is called the gray level or intensity of the image at any coordinate pair (x, y) . In this case, when f values of x , y , and amplitude are finite and discrete, the digital

image is known. The key components of DIP systems in Figure 1.2 are:

- Image Acquisition
- Storage
- Processing
- Recognition
- Display and Communication interface.

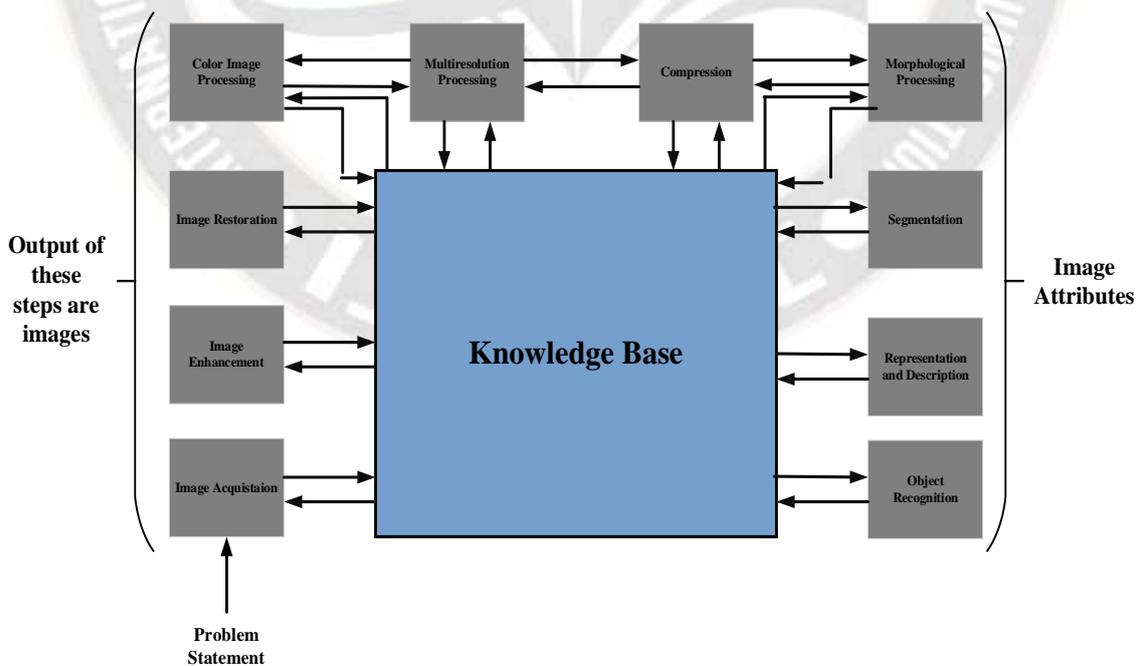


Figure 1.2 Block Diagram of Digital Image Processing System

2. LITERATURE SURVEY

Hatamizadeh et al. (2019) Suggest limited CNNs for clinical images division. The networks are built to display organ-limited data, both through a specific branch edge and edge-conscious conditions of misfortune and a trained start to completion. The authors conclude that the BraTS 2018 dataset is sufficient to split the mind tumour errand. The work shows that the method results in more and more trustworthy divisions, making a progressively broad application to clinical segmentation promising. The authors decided to use the BraTS 2018 data to make the approach to the division of mind tumours feasible. The conclusions indicate that, in comparison to well-known U-Net and V-Net networks, the system produces increasingly precise divided yields with ne-grained limits.

Liu et al. (2019) A proposal in view of the cell-level structure framed by a radical design search zone to look at the system-level structure; The authors present a research area on a system level, which combine different frameworks and generates a concept that allows expert engineering research (3 P100 GPU days on cityscapes). They show that the planned Cityscapes plan, the PASCAL VOC 2012 datasets and the ADE20 K datasets can be rendered feasible. Auto-DeepLab, engineering specially searched for the semantic image division and achieved state-of-the-art effectiveness without pre-training ImageNet.

Stan et al. (2019) The method of measuring the thick induction for CRF is converted into CNN operations, which are then defined as layers of repetitive neural networks. Shows that presentation can be enhanced by preparing NNs with a greater number of littler images checked with the fixed information preparation calculation. The optimal image size and sum of the image preparation are recognized for the XCT and SS data sets. Furthermore, the application of the most notable XCT and SS-NNs in related datasets has evaluated NN transmission. While the underlying divisions have been successful, fundamental changes to the raw images have improved NN execution.

Nascimento et al. (2019) The purpose is to develop a model that identifies deliveries in satellite images as rapidly as is reasonably expected. The aim is to provide knowledge about how moving learning will help to

establish modelling for the organization and division of images. The authors propose that the issue be solved together by two neural networks. First, the authors use a neural network convolutionary classification that channels images with ships. The authors use the U-Net scheme to allow the boat areas to benefit the same number of boats as the Image. The authors interpreted the sharing of learning to use previous frameworks and (pre-preparation) models to speed up the creation of deep neural networks.

Cirillo et al. (2019) Uses a mechanized time-free consumption range forecasting system using deep convolutionary neural networks (CSN), which are the best in the AI class artificial intelligence (AI) method. Shadowing images from the TV camera: VGG-16, GoogleNet, ResNet-50, and ResNet-101. Deep forms of consumption, like skin-and-makeup traditional, have been impaired within the first few days. Ultimately, the best 10-overlaps cross-authorizations obtained with ResNet-101 are 81.66, 72.06 and 88.07% of the results for average, least and maximum precision, and 90.54, 74.35 and 94.25% for each form of individual consumption. The performance was assessed and after the injury the clinical report was gathered. The use of AI is thus promising to meet requirements on consumption depth and thus can be an effective tool for monitoring therapeutic choices and improving wound treatment.

Lee et al. (2019) Propose a new semi-computing dataset age structure for the ultimate purpose of deep learning for a heart division. The authors use this model, prepared freely available from the Challenge for the Segmentation of Robotic Instruments, in order to generate data sets more accurately and faster in different circumstances in order to use a Watershed Segmentation model. The authors use two advanced techniques for heartfelt division. The authors show the capacity of the proposed frame to provide a powerful division quality by tests using the separate successions of laparoscopic Images.

3. Objectives

The goals met by the thesis are listed as follows:

- Preprocessing and analysis of Satellite Images
- Performance Analysis of Machine learning based image difference detection

methodologies.

- Performance Analysis of proposed system under parametric variation for various sample of images
- Development of PCA based image difference detection and segmentation for satellite images.

4. PROPOSED METHODOLOGY

Pre-processing, feature extraction, classification, and accuracy testing are all parts of the classification process.

4.1 Pre-processing

Geometric and atmospheric corrections are part of the pre-processing of satellite data. This study uses a variety of image-enhancing techniques. The colour photos used in this study were transformed to grayscale versions before being used in the study. By reducing the lighting and background effects, a specific filter increases the image's contrast.

4.2 Feature Extraction

Extraction of Feature Sets There must be enough training samples to ensure accuracy, and the classification system must be informative, exhaustive, and severable for each class to function well [4]. In this study, PCA is employed to extract features. Satellite photos of 80x80 squares are used to create a training set for the algorithm. 50 photos made up the practise set. The patterns of settlements in the area were used to capture these photos for use in training. In order to keep track of the Eigen vectors and Eigen values of training images, a matrix is created. This is classified as a feature. PCA is utilised in the training phase of feature extraction. The (MXN) training images are transformed into (LX1) row vectors in the first step. A 6400X1 row vector is generated from an image with a resolution of (80x80).

Step 2: Using K row vectors, the mean settlements vector is determined. Each training image is normalised using this mean image.

$$\Psi = \frac{1}{K} \sum X_i \quad (4.1)$$

Where $i = 1 \dots K$

Step 3: From each training picture X_i , a new normalised matrix is created by subtracting the mean settlements vector.

$$\Phi_i = X_i - \Psi$$

(4.2)

Step 4: A data covariance matrix C is calculated by multiplying matrix Φ with its transpose matrix Φ^t .

Step 5: To find the covariance matrices of a set of data, multiply the original matrix by the transpose matrix t .

The covariance matrix C is transformed into an image space by selecting a selection of the most highly valued eigenvectors. This experiment uses the highest values from each image to create a final matrix that is used to recognise images.. Land cover maps can be generated using photographs taken by satellites because they cover much of the planet's surface and provide a wealth of information. [6] Such data necessitates the use of automated and efficient classification. According to [7], the classification of land cover is critical for both scientific and societal purposes, and satellite photos are ideal since they include a lot of data and cover a large area in one image. Classifying settlements from non-settlements is a two-tiered endeavour. Using the Eigen vectors of each image in the training set and the Eigen vectors of the test image, a decision is made based on the smallest Euclidean distance between them. In this study, images with dimensions of 80x80 and 40x40 were put to the test and evaluated. When it comes to categorising the settlements, PCA's recognition phase serves as a classifier.

Recognition phase of PCA consist of the following mathematical steps.

Step 1: Each test image ' Γ ' is normalized by calculating $\Omega = (\Gamma - \psi)$ (4.3)

Where ψ is the mean image of all training images.

Step 2: A new image is categorized by calculating projection on Eigen-space by:

$$\varphi = \sum (\Omega_i \Omega_j) \quad (4.4)$$

Step 3: A threshold is defined to classify test images. If threshold T matches with the threshold \check{T} of training space then settlement is recognition occurs.

The preprocessing phase uses the following performance metrics to analyze the efficiency of the enhancement algorithm.

Peak Signal to Noise Ratio (PSNR)

To determine the quality of an enhanced image, Peak Signal to Noise Ratio is employed as the most essential

performance metric. PSNR is frequently utilised as a comparison between an original and a compressed image quality measurement. An improved compressed or reconstructed image is achieved by increasing the peak signal to noise ratio (PSNR). The mean square error must first be determined in order to calculate the PSNR.

$$PSNR = 10 \log_{10} \left[\frac{R^2}{MSE} \right] \quad (4.5)$$

Mean Square Error (MSE)

Rows and columns are the input photos' row and column counts in the equation above. The following equation was used to calculate the PSNR for the grayscale images.

$$MSE = \frac{\sum_{m,n} [I_1(m,n) - I_2(m,n)]^2}{m * n} \quad (4.6)$$

PSNR and MSE are the same for colour images with three RGB values per pixel, except for the MSE, which is the sum of all squared value differences divided by three times the image's size.. PSNR varies from 30 to 50 " " dB, with higher values indicating better video compression and lossy image quality. Here is the PSNR for colour photos with three colour components, R,G,B.

$$PSNR = 10 \log_{10} \left[\frac{255^2}{\frac{MSE(R) + MSE(G) + MSE(B)}{3}} \right] \quad (4.7)$$

The sample training set could also be transformed in the same way to produce a new sample free of the outlier pixels' influence. The histograms of the Principal Component histograms were used to segment the pseudobands. The Confusion Matrix was used as a control sample data set to validate the approach. To help with feature segmentation for the selected class, you can utilise the generated image as a mask.

5. RESULT ANALYSIS

5.1 Process of Classification

Pattern recognition, supervised learning, and prediction are all terms used to describe the process of classifying. There are various specified classes to which data can be assigned, thus constructing a technique to do that is part of the job. In order to identify the classes, it applies a rule, a boundary, or a function on the sample's attributes. Databases, text documents, web documents, and so on can all benefit from classification. Classification is regarded as a difficult subject with a wide range of potential study questions. Protein secondary structures, credit card transactions, predicting tumour cell benign or malignant, grouping emails as spam and non-spam, and categorising news stories into various subcategories are just some of the uses of this technology. Because of the following reasons, it is deemed difficult: In today's information-obsessed world, it is nearly impossible to find what you need because of the sheer volume of data available.

A large amount of data is stored, which increases the size and complexity of the database that must be evaluated. The enormous number of "dimensions" or "features" in the databases further complicates the classification process. An example of an elementary classification model is depicted in Figure 5.1. Collection of features arranged in row-wise order is input data for classification task (records). There are two attributes for each record: an attribute set (X) and a special attribute (Y), known as the class label (sometimes referred to as a group or target feature), which is the tuple (X,Y). Learn the target function f that maps each attribute to one of the predetermined class labels, and you'll be done with classification. For the following purposes, the goal function is known as a classification model.

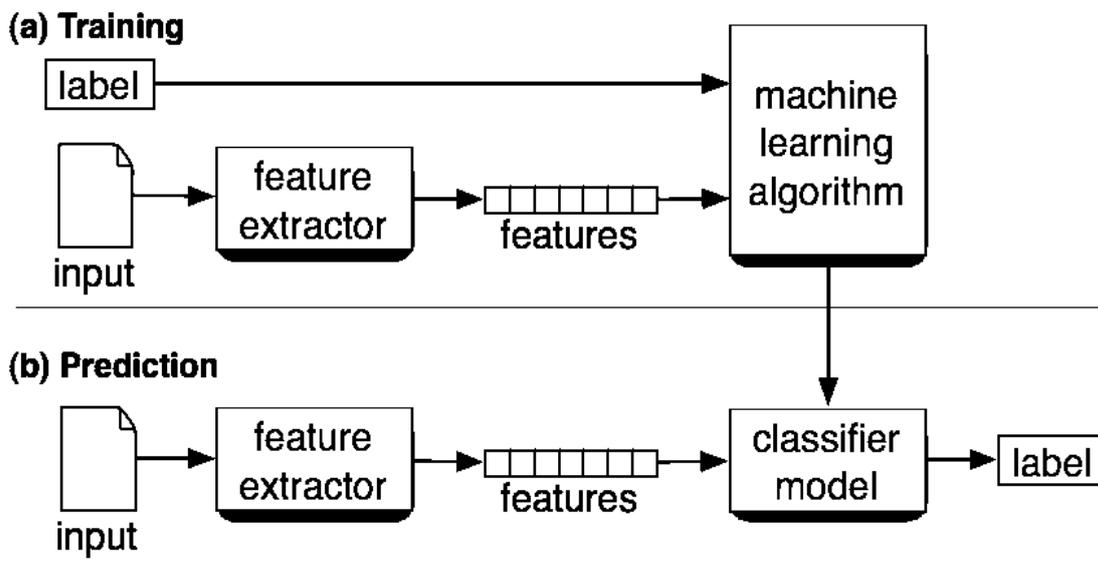


Figure 5.1 Classification Model

For the purpose of being able to use the model to forecast the class of objects whose class label is unknown, classification involves discovering a set of models (or functions) that characterise and distinguish data classes or models. The model is the outcome of analysing a set of training data (i.e., data objects whose class label is known).

There were four stages to the investigation:

A training dataset is created. Images were created for each class with the same ground resolution and radiometric information as the original ones, but specified only on the pixels of the data training set for each image set.

Eigenvectors are extracted from images that contain samples of pixels. To create an image space for the selected class, we analysed the four photos to find four Eigen vectors.

Relative image transformation is applied to the images. Using the first three Eigenvectors, the data were translated into a new space (the feature space) from their

original bands (Red, Green, Blue, and Near Infrared). As coefficients in a linear combination of bands, Eigenvectors were used for the transformation. Linear combinations of the original images from each of the Components (or pseudo bands).

Threshold values are used to mask. For the Pseudo bands, the Principal Component Histograms of the training data set were used to determine threshold values for segmentation.

It is possible to use classification to anticipate the class label of data items in advance. However, class labels may be preferred by some users in many applications due to the possibility of some data being missing or unavailable. This is most often the case when predicting numerical data, and it's why the term "prediction" is so commonly used. There are many different ways to forecast data values, but the most common is to focus on data value predictions rather than class label prediction. Recognizing trends in distribution from available data is also part of the prediction process.

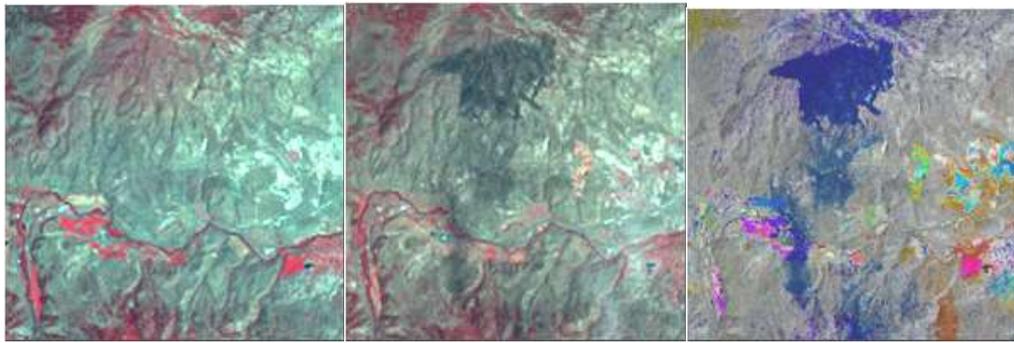


Figure 5.2 Analysis of Labelling of Image Difference from Satellite Image- Sample-1



Figure 5.3 Analysis of Labelling of Image Difference from Satellite Image- Sample-2



Figure 5.4 Analysis of Labelling of Image Difference from Satellite Image- Sample-3

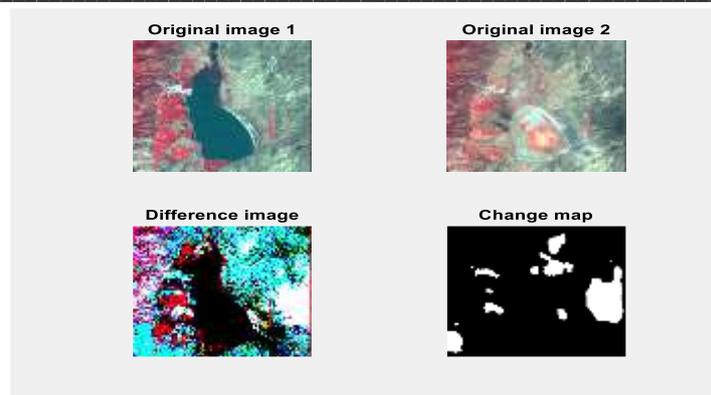


Figure 5.4 Implementation of Proposed Methodology- Sample 3

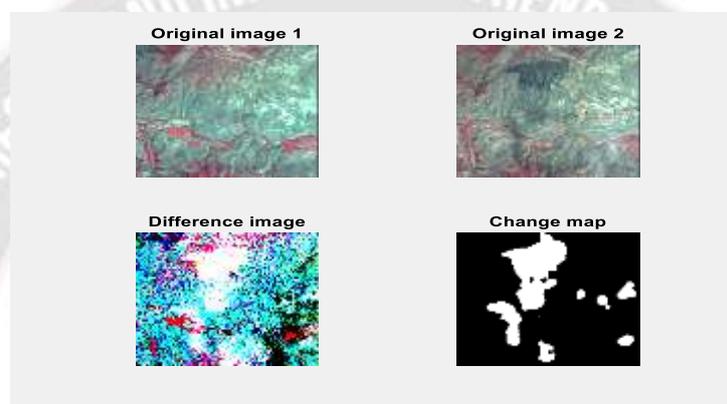


Figure 5.5 Implementation of Proposed Methodology- Sample 1

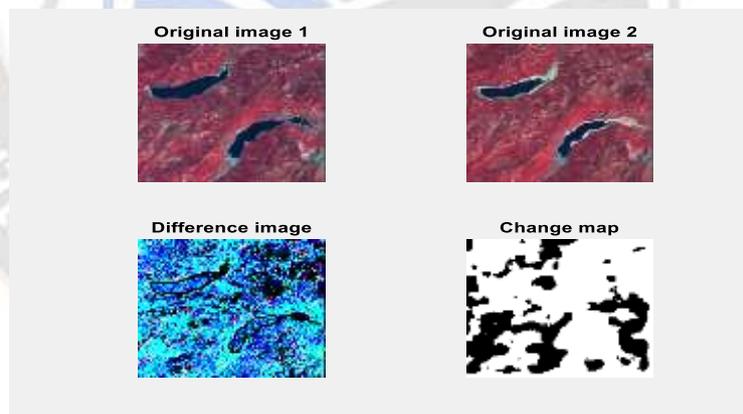


Figure 5.6 Implementation of Proposed Methodology- Sample 1

Table 5.1
Analysis of MSE and PSNR

Sample	MSE	PSNR(dB)
1	126.2613	27.1181
2	125.8301	27.1329
3	76.1762	29.3126
9	3.2284	43.3474
12	1.3385	46.8646

Table 5.2

Comparison of PSNR Value for Proposed Work and Existing Work

Sample	PSNR (Existing)	PSNR(Proposed)
1	24.1022	27.1181
2	25.2071	27.1329
3	27.0234	29.3126
9	41.2178	43.3474
12	43.4092	46.8646



Figure 5.7 PSNR Value for Proposed Work and Existing Work

Table 5.3

Comparative Analysis of Existing Work and Proposed Work

Parameters	Existing Work	Proposed Work
Type of Classifier	K Means Clustering	Principle Component Analysis
Type of Input	Satellite Image of Single Class	Satellite Image of Multi Class
Type of Output	Object Identification	Difference Image+Segmentation+ Change Map
Applications	Identification	Identification and Surveillance
Comparison Parameters	PSNR	PSNR and MSE

The Principal Component Analysis (PCA) was used in this study to develop an automatic classification system for high-resolution photographs based on the sample training dataset. The proposed approach, based on the observed results, enables for the effective segmentation of important features (road and rail network and associated land). In order to get the best results, it is important to choose the right thresholding mask. However, the PCA accuracy assessment compared to the Maximum Likelihood technique highlights the goodness of the suggested method for the selected test class. The completed road and rail network is useful for updating maps at a medium size, however some

extracted regions (such as adding bituminous covers) can affect how the network is updated.

6. CONCLUSION & FUTURE SCOPE

6.1 Conclusion

Settlements in satellite data may be accurately identified using PCA, which is a simple and effective classifier. Because of its dimensionality-reducing nature, PCA is able to manage the high-dimensionality of satellite data. Urban planning, engineering, and management studies around the world can benefit from the classification results. Structured and unstructured settlements can be

subdivided using Principal Component analysis. More than two land use classifications can be classified using the proposed method. Classification is used to estimate population size, detect damage, and track changes.

6.2 Future Work

Engineers constantly work on software for detection and images processing. The segmentation of images is an important method. This method is developed and supplemented by many scientists and researchers. In order to improve the accuracy of the proposed scheme, hybrid approaches may also be implemented

- Classification scheme of adaptive neuro fuzzy inference.
- Inclusion of the profound classification system learning system.
- Classification framework in real-time growth.
- Inclusion of Internet of things for improved applications and a real-time hardware interface system.

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