# Super-Resolution for Remote Sensing Applications Using Deep Learning Techniques

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By

G. Rohith and G. Lakshmi Sutha

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**Dedicated with Extreme affection and Gratitude to**

The Almighty

My parents Mr. S. Giridharan and Mrs. G. Hemamalini

My research supervisor Dr. G. Lakshmi Sutha
(alias) Lakshmi Sutha Kumar

The editors and reviewers of the journals of my published works

&

My well-wishers

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# About the Book

Satellite imaging processing is commonly used for Land Use Land Cover Change (LULCC), cloud detection, and other atmospheric applications. Motion blur from a slow shutter speed, sensor noise, lens blur, and sensor ageing are unusual Remote Sensing (RS) issues in addition to aliasing, optical distortions, insufficient sample densities, and other factors that can affect sensors over a period of time. Building image processors and optical components to address the above mentioned RS issues and interpretability issues is costly. Optical Super-Resolution (SR) exceeds the diffraction limit of devices, whereas the geometrical SR technique boosts the digital image sensor resolution. Sensor limitations and pre-processing processes contribute to imperfect pattern or object recognition in RS images. During that period of time, significant information may be lost. In such cases, a technique can be modelled that enhances feature clarity and resolves objects to their maximum size.

Super-Resolution (SR) is a technique that increases an image's smallest spatial details by increasing the sensor resolution to the same quality without upgrading the image chip. SR increases Ground Sampling Distance (GSD) by reducing picture spatial resolution and visible features. SR upscales and enhances spatial details for a visually pleasing image. Several spatial domain approaches are used to increase object clarity. Deep Learning (DL) may learn unsupervised from unstructured or unlabeled data and improve picture detail. In this SR-based research, DL components in feature extraction for minute detail improvement and classification consequences are studied. This research work explores the DL components to extract satellite image characteristics and examine their classification influence. The research areas are categorized into three applications; (1) Pansharpening applications, (2) Vegetation and agriculture detection applications, and (3) Categorical classifications and decision-making tool applications. SR approaches based on DL analysis, SRCNN, FSRCNN, VDSR, DRCN, LapSRN, SRResNet, Meta-SR, and SRFBN based on dense residual networks, using Deep Convolutional Neural Networks, are found to be ideal for pansharpening applications. Deep Learning-based SR techniques such as SRFBN and EDSR are strongly recommended for improving pansharpening and vegetation signature identification. The state-of-the-art DL-pretrained classifiers have been examined for categorical classification: AlexNet, VGG-16, GoogleNet, ResNet34, ResNet-50, ResNet-101, ResNet-152, VGG-16, VGG-19, CNN (GoogleNet) +LSTM, Mobilenet (v3), and DenseNet-121. According to the results of the study, ResNet-50 and GoogleNet DL are both good choices for categorical categorization. A SR based decision-making tool and a 13-layer deep CNN for categorical classification between two spatial signatures are proposed to classify raw panchromatic pictures categorically. The DL pretrained/modified versions of these classifiers are compared to these two designs to validate the effectiveness of the SR based decision-making tool and categorical classification (CNN) network.

The datasets investigated in this research, in addition to the UC Merced and Eurosat datasets, are:

- 3-band pre-processed datasets such as Set5, Set14, BSD100, Urban100, etc. are extensively used for SR, vegetation identification, and category classification.
- Multi-band pre-processed datasets: SENTINEL-1 and 2, Landsat-7, etc., and three-band pre-processed datasets: RSSCN7, MNIST, Optimal-31, NWPU-RESISC45, CIFAR 100 (e.g. multispectral and hyperspectral datasets), etc.
- Non-commercial and commercially accessible RS datasets (two band preprocessed panchromatic pictures; three band RGB colour and four band multispectral images).

Visual perception and quantitative analysis are used to evaluate the proposed system. Qualitative analysis is carried out by viewing picture attributes such as edge sharpness, pattern clarity, texture uniformity, better image integrity, and increased spatial information, all through the lens of human visual perception. Both reference-based and non-reference measures are assessed quantitatively. SR approaches are used in this study to improve the smallest spatial details in images, lower the cost of imaging sensors, and make it easier to find and classify signatures.

***Keywords:*** Deep Learning; Remote Sensing Applications (RS); Super-Resolution (SR); Pansharpening; Categorical Classification; Ground Sampling Distance (GSD);

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# ABBREVIATIONS

| | |
|---|---|
| **ARVI** | Atmospheric Resistant Vegetation Index |
| **BDSD** | Band Depended Spatial Detail |
| **BRISQUE** | Blind/Reference less Image Spatial Quality Evaluator |
| **CC** | Cross-Correlation |
| **DL** | Deep Learning |
| **DPI** | Dots Per Inch |
| **EVI** | Enhanced Vegetation Index |
| **FSIM** | Feature Similarity |
| **FVC** | Fractional Vegetation Cover |
| **GAN** | Generative Adversarial Networks |
| **GMI** | Gain Mutual Information |
| **GNDVI** | Green Normalised Difference Vegetation Index |
| **GSD** | Ground Sampling Distance |
| **HR** | High-Resolution Image |
| **IFC** | Information Fidelity Criterion |
| **IFOV** | Instantaneous Field Of View |
| **LAI** | Leaf Area Index |
| **LR** | Low-Resolution Image |
| **MI** | Mutual Information |
| **MS** | Multispectral |
| **MNLI** | Modified Non-Linear Index |
| **MOS** | Mean Opinion Score |
| **MSAVI** | Modified Soil Adjusted Vegetation Index |
| **MSE** | Mean Square Error |
| **NDVI** | Normalized Difference Vegetation Index |
| **OSAVI** | Optimized Soil Adjusted Vegetation Index |
| **PAN** | Panchromatic |
| **PIQE** | Perception-based Image Quality Evaluator |
| **PPI** | Pixel Per Inch |
| **PFOM** | Pratt's Figure of Merit |
| **PSNR** | Peak Signal to Noise Ratio |
| **RDVI** | Renormalized Difference Vegetation Index |
| **RS** | Remote Sensing |
| **SAVI** | Soil Adjusted Vegetation Index |
| **SNR** | Signal to Noise Ratio |
| **SISR** | Single Image Super Resolution |

| | |
|---|---|
| **SR** | Super-resolution |
| **SRCNN** | Super Resolution Convolutional Neural Networks |
| **SRFBN** | A Feedback Network for Image Super Resolution |
| **SSIM** | Structural Similarity |
| **TDVI** | Transformed Difference Vegetation Index |
| **TVI** | Transformed Vegetation Index |
| **VARI** | Visible Atmospherically Resistant Index |
| **WDRVI** | Wide Dynamic Range Vegetation Index |

# CHAPTER 1

# INTRODUCTION

## 1.1. PREAMBLE

Disaster and pollution monitoring, geology, and resource exploration use remotely sensed images from satellites to assess key information on the ground. High-resolution (HR) images improve satellite remote sensing capability in analysis and processing applications. Due to image sensor limits, optical system aberration, air disturbance, movement, and imaging system noise, Remote Sensing (RS) images might get distorted. The other critical limitations of the imaging and devices that make the RS images get distorted are:

- The presence of optical aberrations and lens blur, which are commonly described as the point spread function, or PSF;
- Insufficient sensor sampling density and aliasing are the critical limits of imaging and devices.
- Low shutter speed causes motion blur.
- Noise due to sensor limitations as well as lossy coding.as a result of transmission and storage limitations.

Increasing sensor density may hinder the applicability and popularity of high-resolution sensors due to shot noise, expensive hardware costs, increased sensor weight, and bulkiness. When measuring pixel arrays, there are two biasing considerations:

**(1) Feature resolution-** Finding the proper number of pixels to identify the feature and achieving statistical significance in resolution power [4].

**(2) Magnification-** Increasing magnification to increase resolving capability requires the observer to account for edge effects [5].

Ignoring the technically viable vs. cost-effective solution trade-off to provide devices with high spatial (or temporal) resolution is a naïve idea. This can be attributed using following hardware tools:

- Reducing pixel size, which tends to cause shot noise to increase as the quantity of light recorded by the device diminishes.
- Enlarging the chip to accommodate a greater number of pixel sensors, which regrettably leads to increasing capacitance.
- Slowing down the shutter speed, which increases noise levels.
- Use of high-precision optics and sensors, which always leads to a rise in the device's price. Reducing pixel size, which regrettably causes shot noise to increase as the quantity of light recorded by the device diminishes.
- Enlarging the chip size to accommodate a greater number of pixel sensors leads to increasing capacitance.
- Slowing down the shutter speed increases noise levels.
- Use of high-precision optics and sensors leads to a rise in the device's price.

Spatial resolution is the largest object size (footprint size) in a remotely sensed picture and area coverage [1]. Higher resolution reduces the footprint. Instantaneous Field Of View (IFOV) determines resolution. IFOV measures ground area depending on the imaging instrument's geometric characteristics [2]. IFOV is based on the sensor's altitude and viewing angle [2]. IFOV enhances spatial resolution. Spatial resolution is sometimes degraded by incorrect focusing, ambient dispersion, and target motion. Spatial resolution is needed to characterise RS objects in a picture [3]. GSD is one technique to understand SR in RS. It's the distance between two pixel centres [3]. Higher GSD values reduce image resolution and information. Measurement challenges with pixel arrays are key for improving the spatial resolution of the RS picture using the SR technique. Sensor resolution may balance resolving and magnification. This research study uses qualitative (visual perception) and quantitative evaluations at various resolutions and up sampling factors,

- To ensure the availability of the pixels to depict tiny form deviations and high representation of the shape characterization at visually pleasing image quality [5].
- To evaluate the effectiveness of the Super-resolution (SR) techniques on the images considered for the test.

## 1.2. CHOICE OF PREPROCESSING SATELLITE IMAGES

Satellite image pre-processing is crucial when an area contains a temporal sequence of pictures. Image pre-processing makes all photos appear like they originated from the same sensor [6]. Visually pleasing RS pictures require spatial and spectral clarity. Noise removal enhances image data interpretation [6]. Apart from the noise removal at the preprocessing stage, the following characteristics need to be considered for visual interpretable images:

**A. Choice of the dataset based on pre-processing:** Using the best satellite picture improves algorithmic processing [7]. Level-0, Level-1A, Level-1B, Level-2A, Level-2B, Level-3A, and Level-3B are standard image quality levels. Level-0 is raw, instrument-resolution data.

Level-1A is like Level-0, where the raw data is with time reference, radiometric, and geometric adjustments. Level-1B is processed at the same resolution as Level-1A. Level-2A has geophysical variables in addition to Level-1A images. Level-3A images are used in this study, which are radiometrically, geometrically, ortho-rectified, and contrast-enhanced. Level-3B datasets from publicly available domains are preprocessed using radiometric, geometric, pseudocolor, and masking for pansharpening (e.g., for clouds, water, irrelevant features). Level-3B photographs are utilised without preparation since they are intrinsically pre-processed with poor line replacement, pseudocolor processing, and masking (e.g., for clouds, water, irrelevant features).

**B. Bad line replacement:** Bad line replacement replaces the missing lines with the above, below, or average of the two lines while performing raster scanning/capturing of pixels from the sensor [8]. Poor line replacement deteriorates the photos' overall quality. In this study, visual perception is carried out by looking at the full image band by band, in order to detect lines or blocks of missing information in each band for additional correction. The pre-processed photos used in this research work are found to not exhibit poor line properties.

---

**Foot Note-1:** [1]http://uregina.ca/piwowarj/Think/ProcessingLevels.html

**C. Radiometric and Geometric Correction:** Radiometric correction corrects radiometric flaws and digital picture distortions, improving brightness and fidelity. Seasonal phenology, ground conditions, and atmospheric factors can produce multi-temporal spectral response variability [9]. While choosing a map projection system and co-registering satellite image data with other calibration reference data, a relationship is established between image coordinate system and geographic coordinate system [10]. Geometric correction uses sensor calibration data, position and altitude measurements, and ground control points to prevent image distortions. It is interpreted from the study that the geometric correction should be accurate to within one pixel of its real position, allowing precise satellite photography spatial measurements and assessments.

**D. Resampling:** Resampling restores the original distorted image by assessing the digital values for the corrected output image's pixels [8, 11]. The resampling method employs original digital pixel values to produce uncorrected image pixel values [8, 11]. Closest neighbour, bilinear, and bicubic interpolation are resampling algorithms. Closest neighbour resampling uses the digital value that is more relevant to the restored pixel than the original pixel. This is the easiest way, but it may duplicate certain pixel values and delete others, consequently deteriorating the quality of the image.

Geometric rectification uses bilinear and nearest interpolation techniques [10]. Bicubic resampling uses the weighted average of the sixteen nearest pixels from the original data values [8, 11]. Bicubic resampling preserves extremes (outside the range) and subtleties (invisible). Bicubic interpolation is a basic step in numerous Deep Learning (DL) based Super-resolution techniques (SR), and cutting-edge networks are compared to it.

**E. Image Enhancement technique:** Image enhancement for visualisation emphasises and sharpens the image characteristics [12]. Traditional picture enhancing techniques include grayscale conversion, histogram conversion, colour composition, RGB and HSI colour conversion, etc., aid in imagery comprehension and visual interpretation [12]. Modifications on radiometric corrections for illumination, ambient elements, and sensor characteristics may not improve the picture for visual interpretation. Image

***EndNote-1:** Fidelity is the difference in energy between the estimated and blurred HR image. Fidelity is qualitatively visualized, (Human visual perception) by comparing input and output picture blurring, artefacts, pattern clarity, etc.

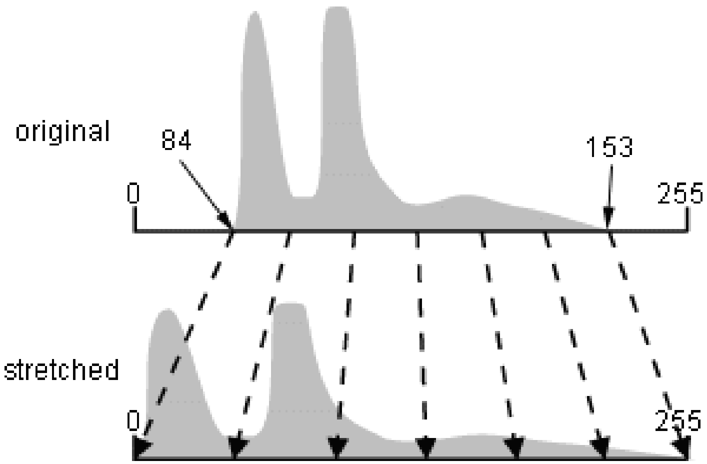


**Fig.1.1:** Linear Contrast Stretch. When the dynamic range is compressed, it becomes easier to see the image. The image is taken from [15].

Fig.1.1 shows a histogram of brightness values that compose an image. The graph's x-axis shows illumination (0–255). The y-axis of [12] shows the frequency of each value.

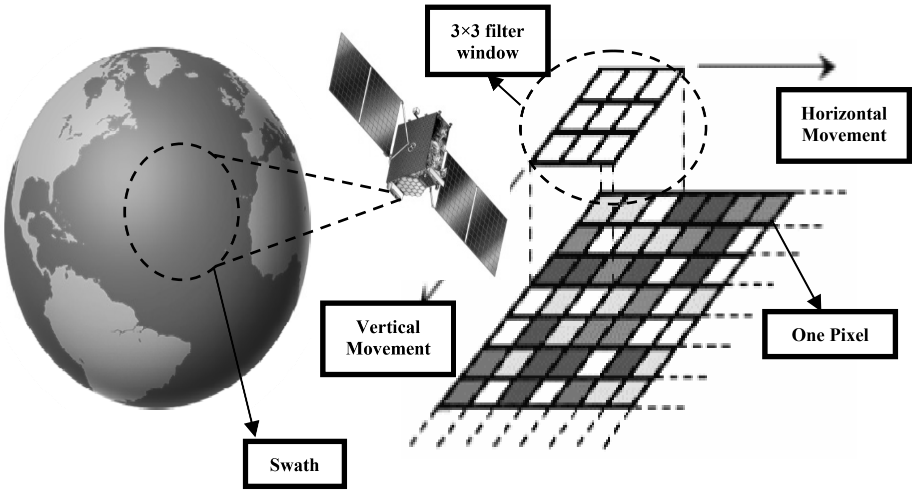


**Fig.1.2:** Spatial Filtering-Illustration. The striding of the 3×3 filter window for each pixel is illustrated.

enhancement for raw images fill a limited portion of the digital value spectrum (commonly 8 bits or 256 levels). Increasing the value range improves target and setting contrast [12]. Raw panchromatic pictures are stretched linearly to boost contrast and details for category classification in Chapter-6 of this research work. The linear contrast stretch involves finding the histogram's bottom and upper limits (the image's minimum and maximum brightness values) and then expanding this range [12–13].

Spatial filtering enhances the quality of photos by adjusting an image's tone frequency. Spatial filters can highlight or hide image details using spatial frequency. Spatial filtering enhances images [14]. High spatial frequencies are present in "rough" textured areas of an image with rapid tone changes [14]. Low spatial frequencies are seen in "smooth" areas with low tone change across pixels. A mathematical procedure using the pixel values below that window is then used to replace the centre pixel with the new value, forming a "window" of size (e.g., 3×3, 5×5, etc.) across each pixel in the image [15]. A window moved one pixel at a time in row and column. After filtering all the pixels in the original image, a "new" image is formed. Spatial filters include low pass, high pass, and directional [15]. The spatial filtering carried out in this study's DL-based Convolution Neural Networks (CNN) is depicted in Fig.1.2. In order to smooth out the artefacts, the primitive step of spatial filtering combines high spatial frequency for edge retention and low spatial frequency for maintaining minute details in the picture.

- **Low-pass filter:** A low-pass filter is used to reduce the amount of fine detail in an image and to emphasise larger, more uniform regions of comparable tones. It improves the look of a picture [16].
- **High-pass filter:** Prior to applying a high-pass filter, a picture must first pass through a low-pass filter. The original picture is then removed from this result, leaving just the high spatial frequency data [16].
- **Directional or edge detection filters**: These filters are used to draw attention to linear objects like field borders or roadways. These filters can also be created to enhance aspects that are targeted in specific directions. In applications like geology, these filters aid in the identification of linear geologic features [16].

On the basis of the issue description and application, suitable high and low pass filters are employed in this research. Additionally, pan sharpening (Chapter-4) and SR-based vegetation identification employ principal component analysis and spectral rationing, respectively (Chapter-5).

- **Principal Component Analysis:** Principal component analysis employs spectral or band ratio methods to capture multi-channel imaging data. This change aims to condense original band information into fewer bands and reduce data dimensionality [18]. The amount of information (or variance) from the original data is minimised [18].
- **Spectral Rationing:** Spectral Rationing is a popular image transformation. Spectral rationing [19] illustrates the small spectrum reactions of different surface coverings. By separating data from two spectral bands, which would typically be masked by changes in pixel brightness, the resultant picture accentuates differences in the slopes of the spectral reflectance curves [19]. When Landsat multispectral Band-7 (Near-Infrared-0.8 to 1.1 mm) is separated by Band-5, plant ratios are substantially greater than 1.0 while soil and water ratios are near to 1.0. (Red-0.6 to 0.7 mm). This helps differentiate plants from other surfaces [20].

**F. Image Interpretation:** Image interpretation is used to categorise characteristics and estimate object visibility [21]. Human visual perception identifies inherent imaging features and objects of interest in high-resolution images [21]. Image size and feature quality determine the importance of a feature. Scale, shape, tonal range, texture, shadow, and pattern are key visual attributes [21]. From Fig.1.3 highlighted in “red” colour bounding box, the crown curve of a tree can predict its high-resolution look. Lower-resolution pictures may have difficulty detecting individual peaks, making texture more significant. In this context, size, form, tone, colour, texture, shadow, and patterns are important.

***(1) Size and shape:*** Size is assessed by looking at objects familiar to the interpreter and comparing their relative size to less familiar objects [21, 22].

Fig.1.3 shows the qualitative analysis of the image’s size, which is interpreted by looking at objects and comparing their relative sizes with less familiar objects. This illustration helps to understand the variations in object size to match the input size for different signatures, giving insight into the qualitative analysis of RS images’ algorithmic processing at 150 percent zooming level in to see the shapes and patterns. Shape is not always diagnostic because different man-made objects, such as the automobile and road,* can have the same shape [21, 22, 23, 24,]. Fig.1.3 shows that man-made objects, like the automobile and the road, are more rectilinear than natural ones.

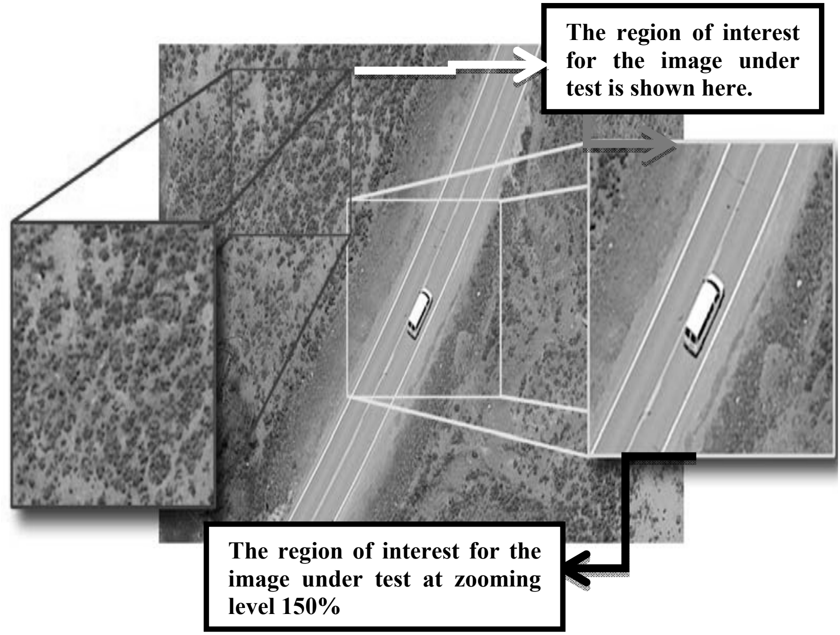


**Fig.1.3: Size descriptors** of the remotely sensed objects- The “red” box indicates the vegetation region, and the “yellow” box indicates the urban region with road objects.

Fig. 1.4 shows that every entity has a form, although the form may not be diagnostic. Urban or rural signatures might reveal a building's signature or texture if visible in a photo. Each feature has a shape. It's seldom a clear diagnosis (i.e., different shapes may have the same type of feature, and various components may have the same form).

***EndNote-2:** The replication of features related to the pictures of objects in a digital image depends on the pixel size. For maintaining scene details and digital representation, a lower pixel size is often advantageous.

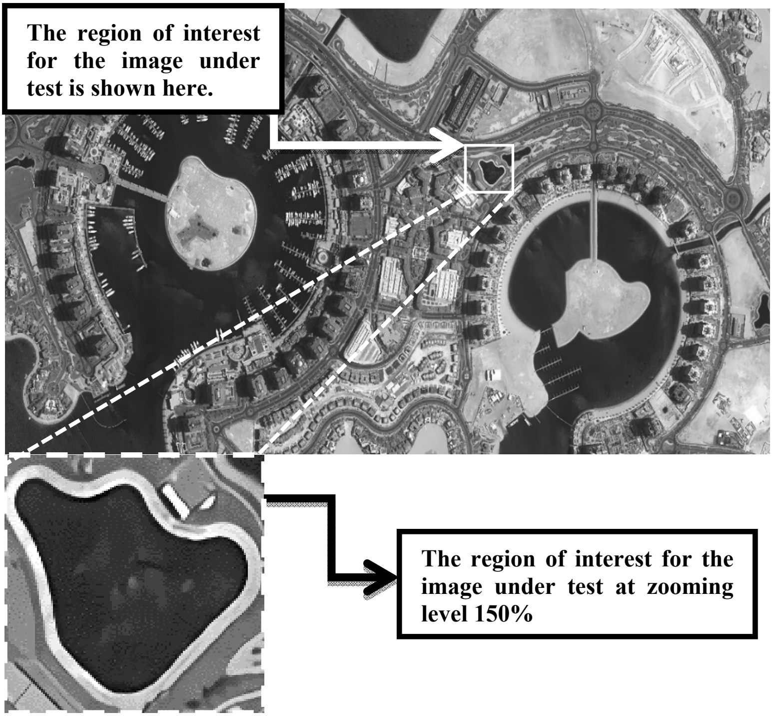


**Fig.1.4: Shape Descriptors:** A picture from the Bhuvan website[2] that depicts shape descriptors. A variety of signature edges, lines, and point representations of remotely sensed objects may be evaluated using the shape descriptors. A precise depiction of sharp edges in shape descriptors aids in determining the processed picture quality.

***(2) Color, tone, texture, and pattern:*** Descriptors of tone and colour reveal several characteristics that have additional reflectance characteristics. The human visual perceptor can identify objects from images using the descriptors of tone and colour, which reveal several characteristics that have additional reflectance characteristics. For instance, light-toned regions reflect more electromagnetic energy (sunlight) than dark features do, which causes them to appear differently in the image. [21, 22, 23].

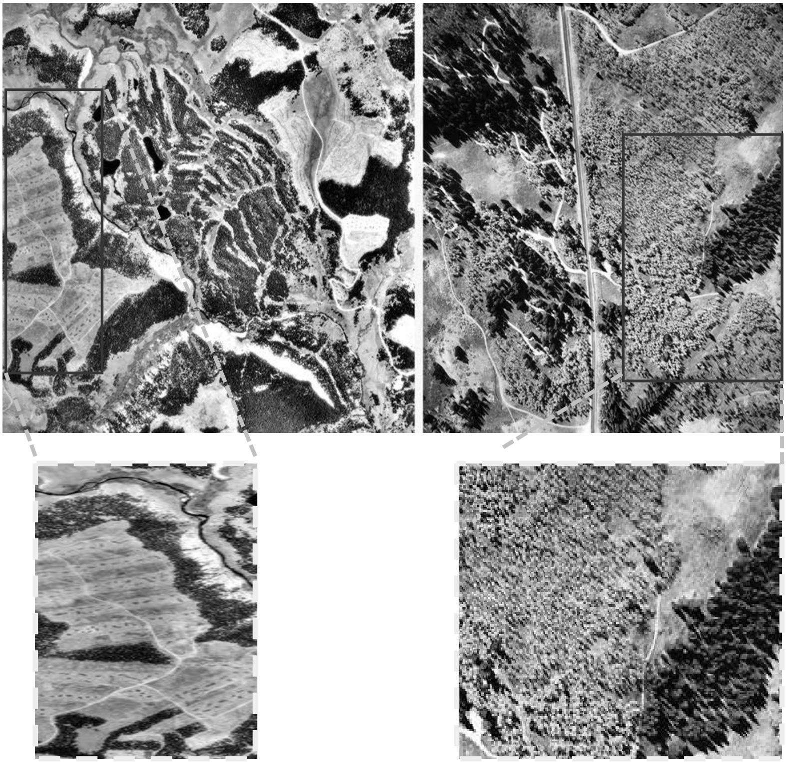

**Fig.1.5:** Tone and color descriptors. The picture, which is from [15], serves as an illustration of tone and colour descriptors. The dashed "Red" circle denotes a zone with distinct, non-overlapping structures. *See centrefold for this image in colour.*

These explanations help understand the colours and nature-related RS images. Therefore, examining the region of interest for any abnormalities added to the output image by the algorithm or the original image. This image shows how hue and signature affect texture. Fig. 1.5 shows how to define satellite picture tone and colour. Fig. 1.5: panchromatic image tone makes it simple to detect roads, trees, harvesting zones, water, etc. Fig. 1.5 demonstrates how road surface formations, senesced grasses, deciduous trees (with yellow fall leaves), and coniferous trees do not intersect visually.