A Hybrid Image Fusion and Classification Model for Land Cover Mapping Using Machine Learning Algorithms

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Abstract : Accurate land cover mapping from remotely sensed imagery is essential for sustainable environmental management, precision agriculture, urban development, and disaster assessment. However, variations in spectral characteristics, sensor noise, and inadequate spatial resolution often reduce the reliability of conventional classification techniques.This research proposes a hybrid framework that combines the QIM-DCT image fusion technique with a PSO-SVM classifier to improve image processing and classification performance. Initially, panchromatic and multispectral images undergo preprocessing to suppress noise and enhance image quality. Subsequently, QIM-DCT is employed to perform efficient image fusion by preserving both spectral fidelity and spatial details through optimized transform-domain coefficient selection. The fused image is then utilized to extract comprehensive spectral, textural, and statistical features that effectively characterize diverse land cover classes. To eliminate redundant information and enhance discriminative capability, feature selection is performed using Mutual Information (MI) and Maximal Information Coefficient (MIC). Finally, a PSO-optimized SVM classifier is developed to automatically determine the optimal kernel parameters and regularization coefficient, thereby improving classification performance and generalization capability. Experimental evaluation demonstrates that the proposed framework produces higher classification accuracy, superior feature representation, and enhanced robustness compared with conventional image fusion and machine learning approaches. The proposed method provides an efficient and reliable solution for high-precision land cover mapping from multisource remote sensing imagery..

Keywords: Remote Sensing, Image Fusion, QIM-DCT, Land Cover Classification, Feature Selection, PSO-SVM, LISS-IV, CARTOSAT-1.

1. Introduction

In remote sensing application image fusion is the most important information from a set of images which is integrated and creates a single input image. The image fusion is used to join the information from two images of the same scene in a single image [1]. This single image includes necessary information about the scene which reduces the amount of data. The image fusion technique should be preserves the information of the input images [2]. The image fusion techniques follow some steps such as decomposition, feature extraction, coefficient calculation, reconstruction and finally, the fused image is obtained which is shown in Figure [1].
Machine learning based algorithms are used for image fusion for obtaining better results. Machine learning algorithm include three types of learning algorithm which are supervised learning, unsupervised learning and reinforcement learning these are used for feature extraction and classification of image fusion based classification.

Image fusion gets the combining information of spatial and domain information from various images such as panchromatic (PAN), Multispectral (MS) and hyperspectral (HS) [2].

Many techniques are used for image fusion such as Discrete Cosine Transform (DCT), Principal Component Analysis (PCA), and Discrete Wavelet Transform (DWT). The image fusion performances are improved by performed pre-processing like intensity conversion and denoising [1] . Figure.2 represents the image fusion techniques. First the images are divided (decompose) into multiple blocks for feature extraction by machine learning algorithm. Then the weight values are calculated for the features based on the features the images fused into single image which are represent as Figure 3.

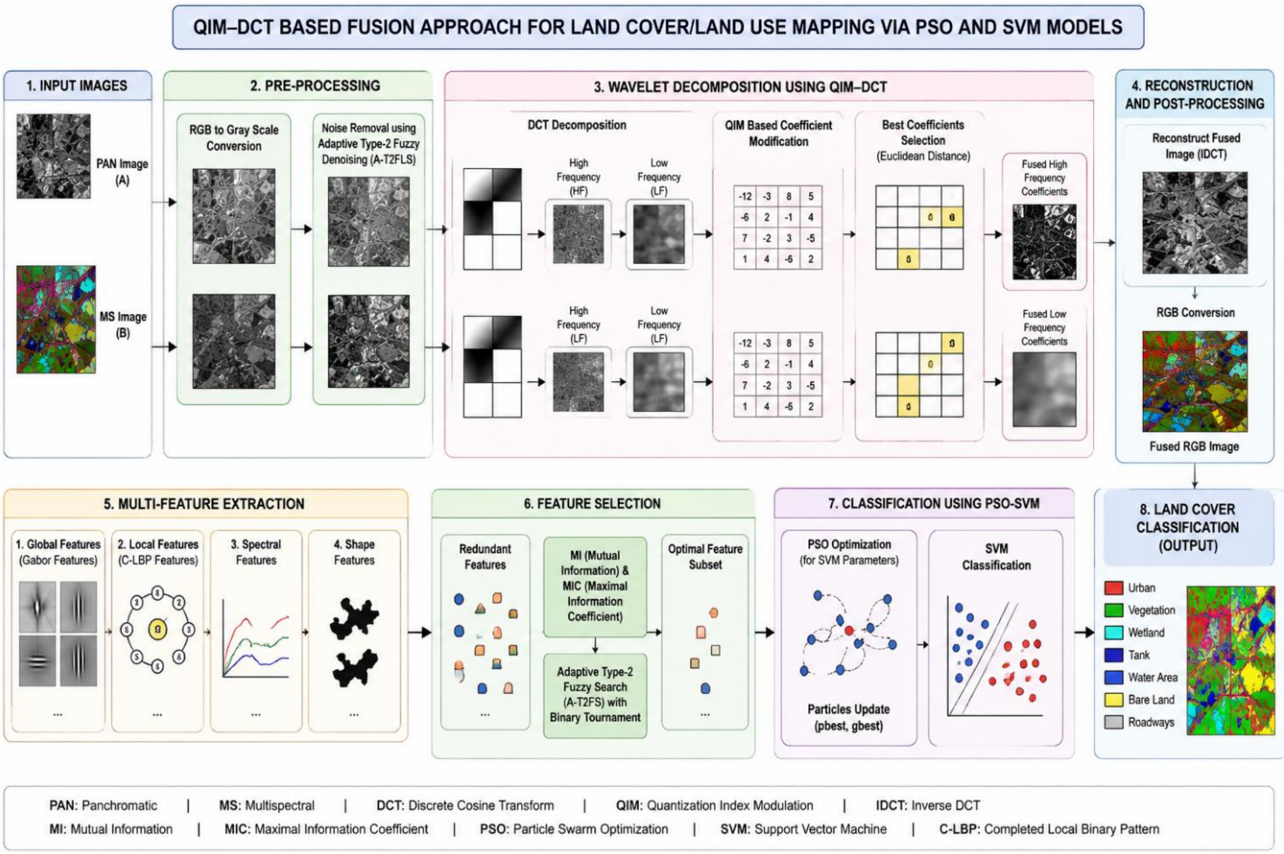


Figure1Processingstepsofimagefusion

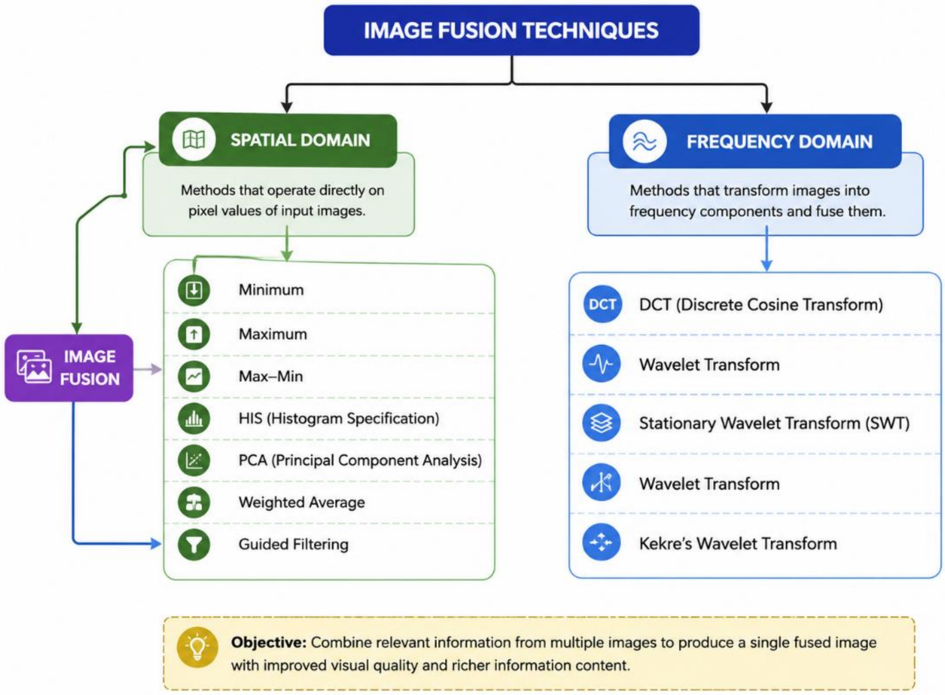


Figure2Imagefusiontechniques

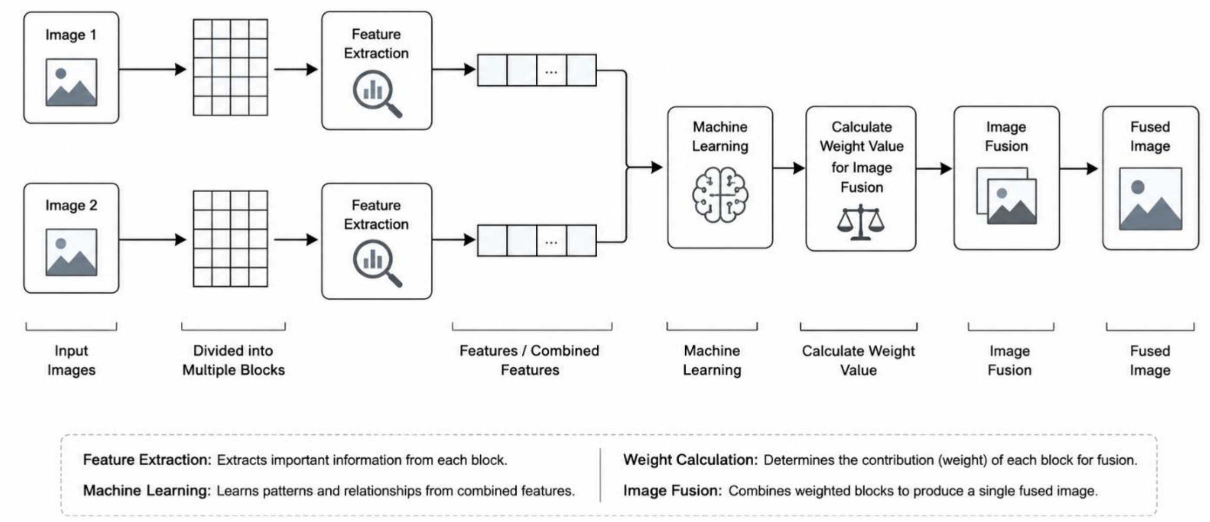


Figure3:Architectureofmachinelearning-basedimagefusion

This research used LISS IV sensor images for providing different resolutions and coverage which is get from the Indian Remote Sensing (IRS) Satellite P6. It is equipped with three sensors: LISS IV, LISS III, and AWiFS. Many filtering techniques are used for removing noise from the images including the median filter, Wiener filter, bilateral filter, and Gaussian homomorphic filter. The pre-processed remote sensing images are classified using machine learning algorithms, including Artificial Neural Network (ANN), Multinomial Logistic Regression (MLR), Support Vector Machine (SVM), and Random Forest (RF)[3]. All the machine learning algorithms are trained for selecting best image pixels for further processing [4]. Using the training information the machine learning based classification methods are classifies the lands into many classes which are defined as follows,

- Urban
- Agricultural land
- Forest land
- Wetlands
- Water body
- Wasteland
- Roadways

2. Literature review

Recent studies have significantly advanced image fusion for remote sensing and land cover classification through the integration of intelligent image processing and machine learning techniques. The study in [8] presented an image fusion algorithm based on the Non-Subsampled Contourlet Transform (NSCT) and Pulse Coupled Neural Network (PCNN) integrated with digital filtering, which effectively preserved edge details and enhanced the quality of fused images. A fuzzy logic and salience measure-based fusion framework was introduced in [9], improving the integration of spatial and spectral information while minimizing spectral distortion. Similarly, [10] presented an adaptively weighted joint detail injection approach that enhanced spectral fidelity and spatial resolution through optimized detail preservation. To improve remote sensing image classification, [11] explored the integration of tree-based kernels with Support Vector Machines, demonstrating improved classification performance. Furthermore, [12] showed that Extremely Randomized Trees provide an efficient kernel-based solution for accurate land cover classification. Deep learning-based urban land cover change detection using Convolutional Neural Networks (CNNs) was explored in [13], achieving superior classification accuracy for very high-resolution imagery. A saliency-driven image fusion technique based on the complex wavelet transform was introduced in [14], effectively preserving salient image features during fusion. Additionally, [15] introduced an image enhancement approach combining an adaptive nonlinear gain combined with the PLIP model in the NSST domain, resulting in improved image contrast and feature visibility. Overall, these studies demonstrate that advanced image fusion, enhancement, and machine learning-based classification techniques substantially improve remote sensing image analysis; however, there is still a need for integrated frameworks that jointly optimize image fusion, feature selection, and classification accuracy.

3. Methodology used

This section outlines the overall procedure of the proposed work for image fusion based classification using remote sensing images in detail. The proposed work includes six consecutive phases which are listed as follows,

- Pre-processing
- Wavelet Decomposition
- Best coefficient selection
- Feature Extraction
- Feature Selection
- Classifications

Wavelet decomposition is performed using QIM and DCT in five stages to classify the fused images into eight classes, including urban, vegetation, wetland, tank, water area, bare land, and roadways. Figure [4] represent the system model of the proposed system.

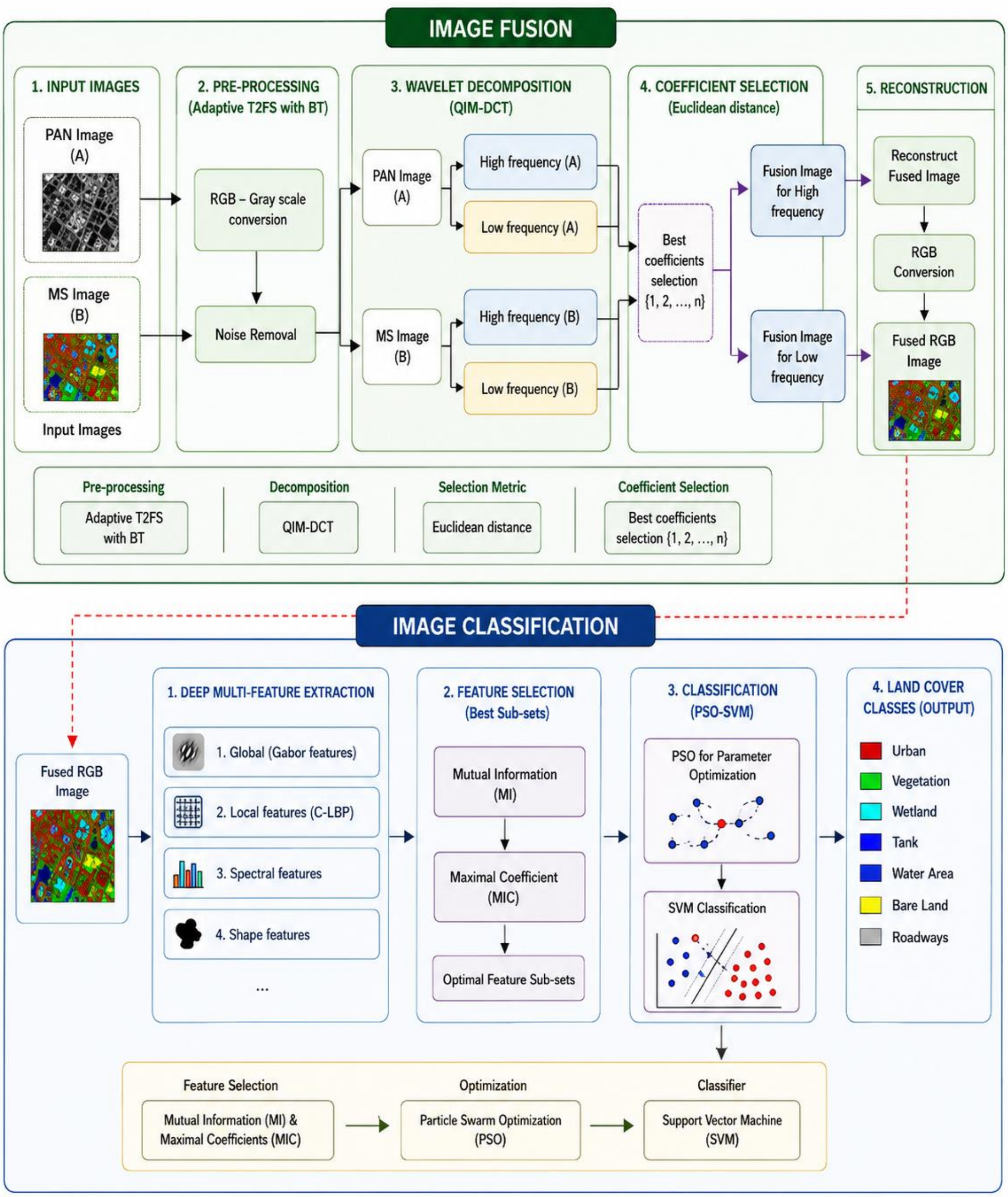


Fig 4

This is the first step of the research work. Pre-processing is an important process in image processing. Every raw remote sensing image contains many artifacts and errors which are removed for obtaining better results. The main objective of pre-processing is to improve the image quality, which removes the distortions (noise, geometric correction, radiometric correction, and atmospheric correction) for further processes [3]. In this work pre-processing includes two processes, such as color conversion and noise reduction, which improve image quality and image fusion accuracy, which also increase land classification accuracy [5].

Color conversion is under preprocessing which is used to improve image fusion performance. For this, color conversion is performed because color images increase the computational complexity. RGB images have three color channels: Red, Green, and Blue. Similarly, CMYK images have four channels: Cyan, Magenta, Yellow, and Black.

The luminosity method was proposed for changing the images from RGB to gray. The calculation of the gray scale is defined as follows,

$0.21R + 0.72G + 0.07B = Gray\_value$ [1]

Equation [1] represents the RGB-to-grayscale conversion, which converts images to grayscale. Figure 4.5 represents the RGB and gray-scale LISS images.

The proposed A-T2FLS with Bayesian threshold is to recover the best quality remote sensing image from the noise remote sensing images with poor quality. In this process, remove noise (Gaussian noise, salt & pepper noise) using Bayesian thresholding with an Adaptive Type-2 Fuzzy System, where the Primary Membership Functions (PMF) represent the good pixels, while the Secondary Membership Functions (SMF) represent the bad pixels. The proposed Bayesian Thresholding method removes the noise from the image from right to left.

Standard T2FLS

Type 2 fuzzy algorithm is introduced by solve the problems of the Type-1 fuzzy system. The limitation of the Type-1 Fuzzy sets, which are defined as follows,

•Type -1 Fuzzy sets utilize uncertain words

•Fuzzy rules contain histogram values that extract the knowledge from a particular group of experts.

•It gives a noisy measurement

•The input source is used to tune the parameters of type-1 fuzzy logic, which provides noisy results

These limitations are overcome by a type-2 fuzzy inference system, which meets membership functions by reducing the rules. The membership function $\mu S\ (x, u)$ of a type-2 fuzzy inference system is defined as follows,

$S = \int x\in X\ [\int u\in Jx(x, u)/u]\ /x,\ Jx\subseteq\mu S\subseteq\ (x, u)\epsilon$ [0,1]………………..[2]

where, Jx represent the primary membership of fuzzy rules and the interval of x between 0 and 1 and u represents the secondary variables and $\mu S(x, u)$ represents the secondary grade. The secondary grade value is equal to one for all secondary fuzzy rules, and s represents the interval of type 2 fuzzy set. Type-1 fuzzy sets is defined as follows,

$Sx = \int u\in Jx(x, u)/u$……………..[3]

The proposed A-T2FLS is used to remove the noise from the gray images. The proposed algorithm includes two steps for removing the noise. The pixels are classified as good or bad based on the membership function. Next, calculate the threshold between good pixels and bad pixels through design PMFs, which is referred by Gaussian Membership Function (GMF), along with the bad pixels are denoised. NH represents the neighborhood pixel, which is associated with $Pij\in I$ with a window size of half filter H. Hence,j and PMF values are

evaluated for every component of the neighborhood pixel. The threshold value is

calculated based on the values of the upper and lower membership functions of T2FLS. This threshold is changed in an adaptive manner. Then the components of NH are classified into bad pixels and good pixels. The conditions of good pixels and bad pixels are defined as follows,

•$If\ (Pij\ (PMF) > bt$ If the iteration is satisfying this condition, then it is classified as a good pixel and forwarded to the next iteration.

•$If\ (Pij\ (PMF) < bt$ If the iteration satisfies this condition, then it is classified as bad pixel, which is removed from the iteration.

where bt represents the Bayesian optimum threshold value, which is adaptively updated. In this work, the focus is on the noise value between [0, 1]. Hence, Pij represent the intensity values $Pij\notin$ [0,1] which are forwarded to the next iteration. Figure 4.6 represents the overall process flow.

The overall workflow of the proposed framework for land cover classification is illustrated in Figure X. Initially, the PAN and multispectral images are pre-processed through RGB-to-grayscale conversion and Adaptive Type-2 Fuzzy Logic System (A-T2FLS) based denoising with Bayesian Thresholding to improve image quality. The denoised images are subsequently decomposed using the proposed QIM-DCT approach, which generates high-frequency and low-frequency components. The optimal fusion coefficients are then selected using the Euclidean distance criterion and utilized to reconstruct a fused image containing enhanced spectral and spatial information. From the fused image, multiple discriminative features, including spectral, texture, shape, local, and global features, are extracted to characterize different land cover classes. To reduce feature redundancy and improve computational efficiency, Mutual Information (MI) and Maximal Information Coefficient (MIC) based feature selection is performed to identify the most informative feature subsets. Finally, the selected features are supplied to a Support Vector Machine (SVM) optimized using Particle Swarm Optimization (PSO) classifier, where PSO optimizes the SVM parameters to achieve robust classification performance. The proposed framework classifies the remote sensing imagery into various land cover categories, comprising urban areas, vegetation, wetlands, tanks, water bodies, bare land, and roadways. The integration of QIM-DCT image fusion, MI-MIC feature selection, and PSO-SVM classification significantly enhances classification accuracy and provides reliable land cover mapping results.

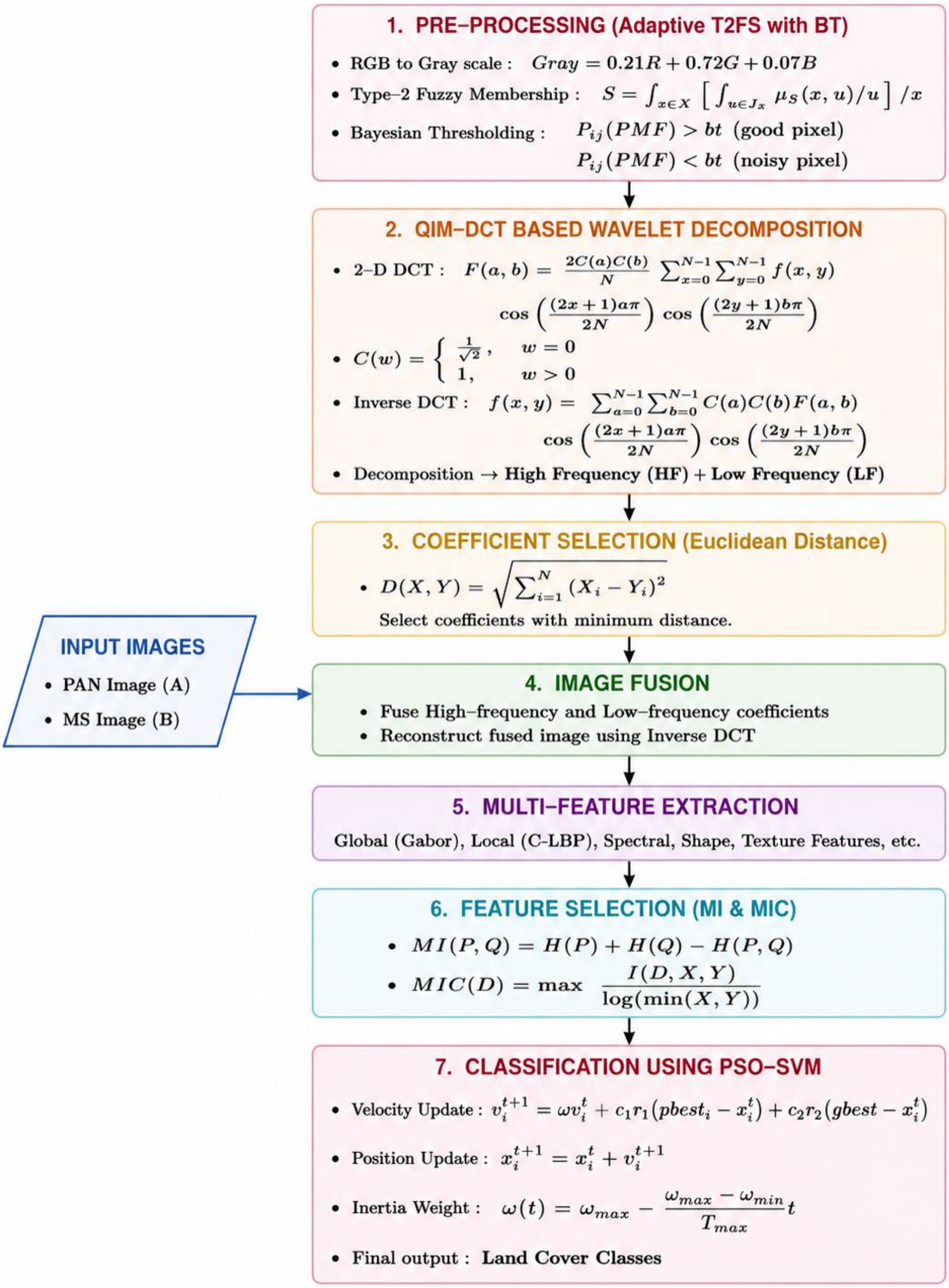


Figure 5

4. Results

This section describes the results obtained using the proposed method.In addition is explains the comparison of the proposed and existing work results. The performances are evaluated using various performance metrics.

In recent years, remote sensing is an emerging technology for capturing images of the Earth from various satellites with sensors. It provides the earth images with various spectral and spatial and time resolutions. For improving the quality of the images this research performs image fusion. In which the multiple images are fused into single image with the high quality and resolution (Spatial and Spectral). This research measures the classification accuracy with respect to two steps such as classification with fusion, classification without fusion. From the comparison result it proved that the proposed image fusion provides better performance compared to without fusion method. The proposed image fusion based method has five benefits which are defined as follows,

•High reliability and robustness

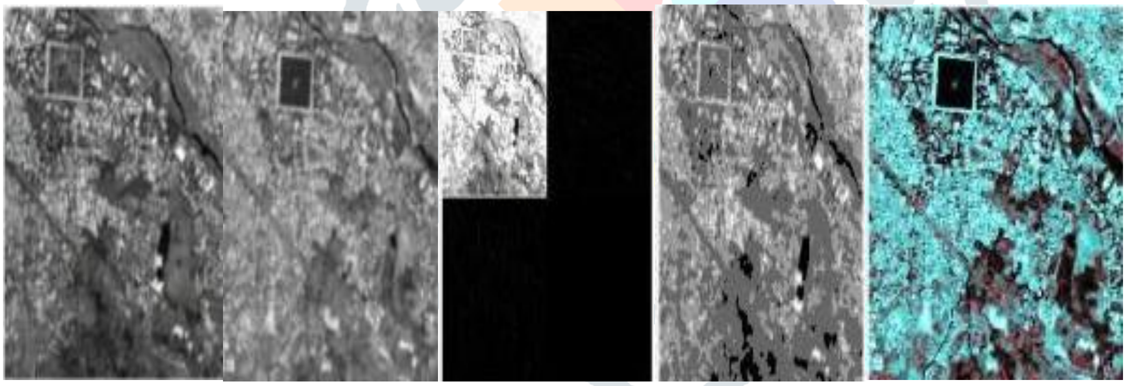
•Improve the time and space observation range

•Improves accuracy and credibility

•Enhance target monitoring and identification

•Reduce redundant information of target image

Table 1 and 2 represents confusion matrix of proposed method with fusion classification and without fusion of PAN and LISS IV image classification respectively. The classification accuracy of the proposed work with fusion is achieved 92.11% and kappa coefficient is 0.89. The classification accuracy of PAN image is achieved 77.73% accuracy and 0.7 kappa coefficient and LISS IV image is achieved 85.02% accuracy and 0.8 kappa coefficient for seven types of land cover like Urban, Bare Land, Vegetation, Tank, wetland, Water Area, and Roadways. Figure 4shows the result of the proposed work.



(A) (B) (C) (D) (E)

Figure 6 Proposed work results (a) PAN image after preprocessing,

(b) MS image after preprocessing, (c) Wavelet decomposing images, (d) QIM images and (e) Fused image

Table 1 Confusion matrix of PAN image using SVM+PSO (without fusion)

		Reference Data							
		No. of Samples	**Urban**	**Vegetation**	**Water Area**	**Bare Land**	**Tank**	**Roadways**	**Wet Land**
Classified Data	Urban	201	155	16	7	7	5	4	7
	Vegetation	127	10	100	4	4	2	2	5
	Water Area	50	4	3	30	2	4	2	5
	Bare Land	45	2	5	2	26	4	2	4
	Tank	14	4	2	1	1	5	0	1
	Roadways	13	3	3	0	2	2	3	0
	Wet Land	44	5	4	7	3	4	1	20

Table 2 Confusion matrix of LISS IV image using SVM+PSO (without fusion)

		Reference Data							
		No. of Samples	**Urban**	**Vegetation**	**Water Area**	**Bare Land**	**Tank**	**Roadways**	**Wet Land**
Classified Data	Urban	201	170	8	5	3	6	3	6
	Vegetation	127	2	110	4	3	2	2	4
	Water Area	50	4	2	36	2	1	2	3
	Bare Land	45	3	3	1	32	1	2	3
	Tank	14	2	1	1	1	8	0	1
	Roadways	13	2	1	0	2	2	6	0
	Wet Land	44	3	2	5	2	3	1	28

Table 3 Confusion matrix for fused image using SVM+PSO

		Reference Data							
		No. of Samples	Urban	Vegetation	Water Area	Bare Land	Tank	Roadways	Wet Land
Classified Data	Urban	201	194	2	0	0	2	1	2
	Vegetation	127	1	120	2	2	0	2	0
	Water Area	50	2	0	45	1	1	0	1
	Bare Land	45	2	1	0	40	0	0	2
	Tank	14	1	1	0	0	11	0	1
	Roadways	13	1	0	0	1	1	10	0
	Wet Land	44	2	1	2	2	1	0	36

This section presents a comparison between the proposed and existing system models. This thesis discusses the results of image fusion techniques, including KNN (K-Nearest Neighbor) [6], HCS (Hyperspectral Color Sharpening) [7], Wavelet Transform [8], and G-RBF (Gaussian RBF Kernel) [9] then compared the classification techniques such as ANFIS [10] , WBCT [9] , MCT [9] and combine WBCT and MD [9]. Table 4 – 7 represent confusion matrix of various existing fusion methods classification results. From the comparison of image fusion, proposed work achieves high performance for spectral and spatial performance metrics. The proposed wavelet decomposition and denoising algorithm are proposed to improve the performance of proposed image fusion method. This work has less computation due to denoising, and gray scale image. It achieves 55.7db PSNR value and 0.3 SA and 0.982 CC and 1.2 SSIM and 0.985 NCC and 50.478 RMSE and 1.2 FMI and 0.956 gradient and 0.984 SCC and 0.985 IE values which lead to high performance for image fusion compared to existing methods. This thesis compares proposed work to existing work in terms of accuracy of user, accuracy of producer, total accuracy and kappa coefficient. It shows that proposed work achieved high accuracy using PSO-SVM classifier for land cover classification. Table 8 illustrates the comparison of image quality between proposed and existing methods using spatial and spectral metrics which shows that the proposed work achieves higher performance compared to existing work. Table 8 illustrates the comparison of accuracy between proposed and existing method in terms of accuracy of user, accuracy of producer, total accuracy and kappa coefficient. Figure 7 illustrates the comparison result of proposed and existing methods such as ANFIS, WBCT, WBCT+MD and QIM-DCT. Sample images classification of fused image, PAN and LISS IV images using SVM+PSO classifications are shown in Figure 8.

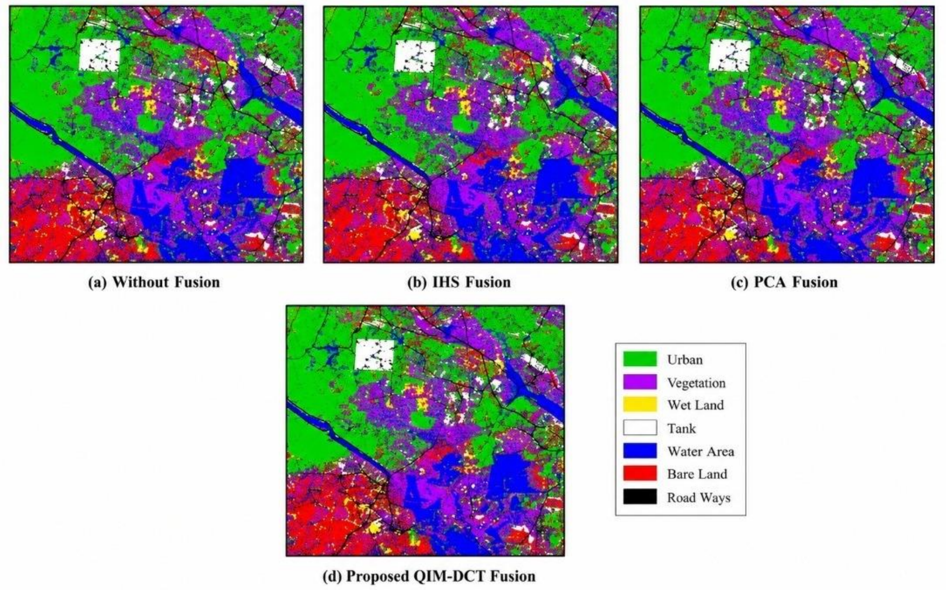


Figure7Classified output using (a) ANFIS,(b) WBCT, (c) WBCT+MD and (d) QIM-DCT

Table8Accuracycomparisonbetweenproposedandexistingmethods

Metrics	ANFIS	WBCT	MCT	WBCT+MD	Proposed SVM+PSO
Accuracyof user(%)	75.37	76.62	79.82	81.63	86.74
Accuracyof producer(%)	75.29	77.83	81.53	83.33	85.96
Totalaccuracy (%)	86.44	88.06	90.08	90.89	92.31
Kappa coefficient	0.82	0.84	0.87	0.88	0.9

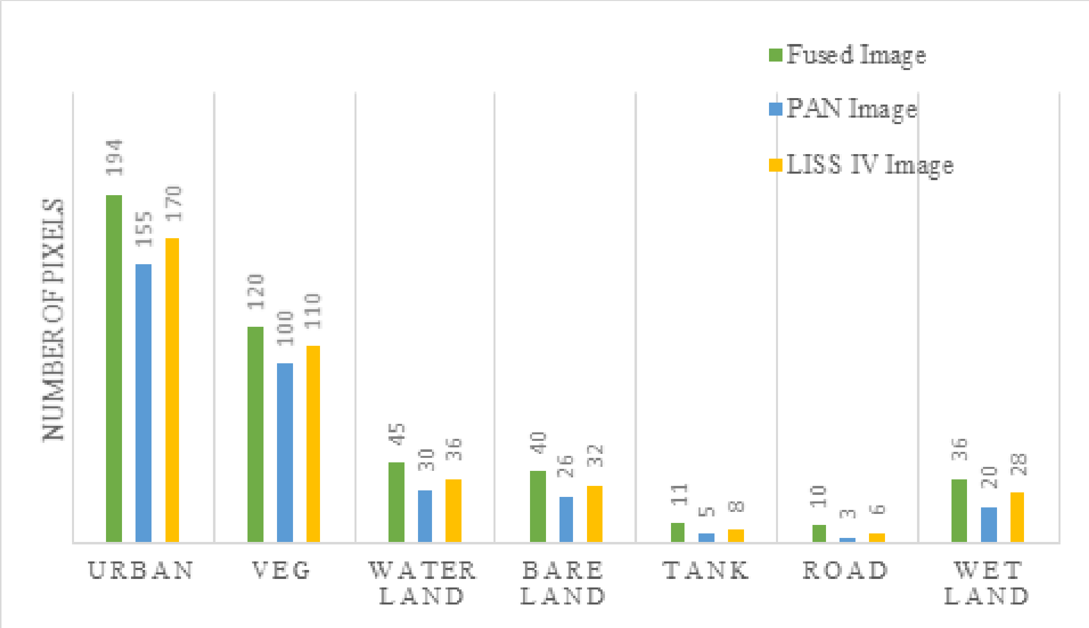


Figure 8 Sample images classification of various image using SVM+PSO

5. Conclusion

The integration of image fusion and classification provides a robust, reliable, and scalable performance in remote sensing images. This research proposed image fusion-based classification for obtaining better performance.

It considers 1000 sample images of size 7X7 taken from single LISS IV for training and 500 sample images of size 7X7 taken from the same image for testing. In that LISS IV sensor MS and PAN images which are captured by IRS P6 and CARTOSAT-1 satellite. These images are captured at Madurai city in Tamil Nadu, India. This thesis proposed image fusion method improves the performance of classification. In addition, this method achieves high performance of image fusion by considering spectral and spatial characteristics. A large number of noisy images achieve poor accuracy during classification, to overcome these issues the proposed work decomposes the images into five levels with 8 directions, which also provides better coefficients by detecting the distance between the images. Finally, the images are fused into a single image, which is then passed to the PSO-SVM classifier for land cover classification. Then the performance evaluation is performed with various performance metrics. The comparison results of the proposed method outperforms existing methods.

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