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Fused LISS IV Image Classification using Deep Convolution Neural Networks

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Abstract

These days, earth observation frameworks give a large number of heterogeneous remote sensing information. The most effective method to oversee such fulsomeness in utilizing its reciprocity is a vital test in current remote sensing investigation. Considering optical Very High Spatial Resolution (VHSR) images, satellites acquire both Multi Spectral (MS) and panchromatic (PAN) images at various spatial goals. Information fusion procedures manage this by proposing a technique to consolidate reciprocity among the various information sensors. Classification of remote sensing image by Deep learning techniques using Convolutional Neural Networks (CNN) is increasing a solid decent footing because of promising outcomes. The most significant attribute of CNN-based strategies is that earlier element extraction is not required which prompts great speculation capacities. In this article, we are proposing a novel Deep learning based SMDTR-CNN (Same Model with Different Training Round with Convolution Neural Network) approach for classifying fused (LISS IV + PAN) image next to image fusion. The fusion of remote sensing images from CARTOSAT-1 (PAN image) and IRS P6 (LISS IV image) sensor is obtained by Quantization Index Modulation with Discrete Contourlet Transform (QIM-DCT). For enhancing the image fusion execution, we remove specific commotions utilizing Bayesian channel by Adaptive Type-2 Fuzzy System. The outcomes of the proposed procedures are evaluated with respect to precision, classification accuracy and kappa coefficient. The results revealed that SMDTR-CNN with Deep Learning got the best all-around precision and kappa coefficient. Likewise, the accuracy of each class of fused images in LISS IV + PAN dataset is improved by 2% and 5%, respectively.

Keywords: Image Fusion, Discrete Contourlet Transform, Image Classification, Remote Sensing Images, Quantization Index Modulation, Deep Convolution Neural Networks.

1 Introduction

Classification of remote sensed image is the method that changes remotely sensed image in to usable products. In that classification process deep learning is a one of the emerging concept in recent year. It is extensively used in huge application such as wireless communications, NLP, computer vision and image processing. In this paper we mainly concentration on classification processes to generating land-cover / land-use maps. Over past few decades Land- cover /land - use mapping mainly using satellite or airborne imagery due to better-quality data availability and accessibility.
Remote sensing image Classification using deep learning used in wide fields of slum detection [12], land cover land use mapping[13,14,15], agriculture land detection and urban planning. In classification feature extraction play a major and important role. To improve classification efficiency automatic feature extraction technique is essential. Feature chosen by human interaction will degrade the efficiency of classification process. So we used deep learning technique in this paper. Image fusion is another recent booming task to improve efficiency of image classification. Many recent research areas focus fusion technique to enhance the quality of the process. In image fusion, the most important information is obtained from the collection of images provided and the resulting single image provides high quality. Many earth-observing satellites can be captured various remote sensing images with more spatial and less spectral resolution panchromatic images (PAN) and more spectral and less spatial resolution multispectral (MS) images [16,17]. Various image fusion techniques yield more spectral and spatial resolution remote sensing images[18,19].
In summary the key contribution of this paper are in four fold: We proposed Deep learning based methods such as CNN for classifying fused image due to automatic deep feature extraction in deep learning. For better result of accuracy identification we used multi model ensemble algorithm with CNN. For enhancing the image fusion execution, we remove specific commotions utilizing Bayesian channel by Adaptive Type-2 Fuzzy System. We show multiple studies for the suggested method that have produced far better outcomes than previous works.
The remaining portion of this paper is sorted as follows. The Section 2 talks about the present principle difficulties of remote sensing image characterization. A short audit of deep learning models and a thorough overview of deep learning based image classification strategies were additionally given. In Section 3 we provide the study area and data used. The technique of proposed work including the image fusion procedure and image order is given in Section 4. In Section 5, the evaluations for the suggested experimental settings with the discussion of findings are shown. Finally, we finish up this paper in Section 6 with concluding remarks and future possibilities.

2 Literature survey

Swathika et al (2018) present a new method called THBMT-FIS to achieve high image visibility and accuracy. To remove light character and dark character they use black and white top hat method. They use Fuzzy Inference Scheme (FIS) to perform image fusion of PAN and MS image[25]. Zheng et al. (2017) uses guided image filtering to fuse GF2 (GaoFen-2) images. It is used for combining feature of two different source images such as PAN and MS image. During filtering process high spectral resolution MS band consider as a reference image for the simulated Pan band. After that filtered image subtract from input PAN image to obtain high spatial details. Finally fused Pan sharpen image obtain by insert high spatial information into each band of the resampled MS image [9].
On 2016 [2] Khatami et al. proposed a study on pixel-based supervised methods for ground cover mapping. They suggested the most powerful Support Vector Machine (SVM) with a total accuracy of 76 percent for many applications (OA). A neural network (NN)-based classification model of about the same performance of 75 percent overall precision was another technique. In that method, single date image classification was done and also SVM consume much more resource. They conclude that SVM used for large area classification problems and big data applications.
Chen et al (2014)[3] proposed Stacked Auto Encoder with Logistic Regression SAE-LR approach to extract deep features for hyper spectral image classification. It is really a dynamic framework for the study of the principal components, the architecture of a deep understanding and regression

of logistics. First they compute deep spectral features through stacked auto encoders and logistic regression classifier used to complete the spectral classification phase. Next they classify Spatial-dominated information by compressing in spectral dimension using PCA, then flattening spatial data and extract layer-wise deep features using AE. At last they proposed a different deep system for learning to integrate the two set of deep spectral and spatial features for acquire highest classification accuracy. Finally they use logistic regression in the bottom layer of a neural network for classification process. They suggest whether deeper features often have greater accuracy of classification, while deep structure can work in reverse as well. The experimental result shows that proposed SAE-LR method provide higher accuracy than RBF-SVM method.

Over past few years, most of the task performed in computer vision, image processing and natural Language processing used most powerful machine learning algorithm is Deep learning. For processing hyperspectral and Multi Spectral images, Deep Learning is one of the efficient methods. Most of the studies show deep learning method used to extracting different land covers types such as road extraction, water body extraction and buildings extraction. Convolution Neural Network is one of the best Deep Learning approach to provide best feature extraction without manual interaction. For high resolution hyper and multispectral image classification CNN algorithm provide high efficiency in spatial and spectral feature exaction [6,7]. To improve classification efficiency, now days another deep learning approaches such as deep convolutional neural networks used through most of researcher. It mainly contains convolution layers and the down sampling layers that provide greater performance ratio compare to other deep learning methods.

Yue et al [4] use hybrid framework based on principal component analysis, deep convolutional neural networks (DCNNs) and logistic regression (LR) for classifying hyperspectral images. In that method deep features of hyper spectral images extract through DCNN. The experimental result shows that proposed method outperform compare to stacked autoencoder-logistic regression (SAE-LR) (Chen Lin et al. 2014)[5]. Kussul et al (2017)[1] proposed new multilevel Deep Learning method for land cover and crop type classification. In that architecture they perform four level of processing to classify multitemporal imaginary. Different Convolution Neural Network such as 1-D CNN and 2-D CNN is a main core of this architecture to extract spectral and spatial features. This architecture is one of outperform ensemble of CNN method to provide better classification of certain summer crop types efficiently.

Rajesh et al (2020) proposed new Object based classification technique [10] considers each image sections as a building chunk for the further image investigation. Specifically the convolutional neural network (CNN) of Deep learning techniques has upgraded the performance of remote sensing image classification due to the dominant perception of reasoning and feature learning. The object based approach can be used to powerfully describe and classify high resolution imagery. A detailed review was proposed by Ava Vali et al. [20] on 2020 based on various deep learning algorithms for land use and land cover classification using multispectral and hyperspectral images. To increase classification accuracy Xiangyong Cao et al use active deep learning method to classify hyper spectral image with the combination of CNN and Markov random field [21]. Liu et al. (2020) proposed band independent encoder-decoder model. It work any level of scaling factors and robust to work with several spectral features of spatial resolution images such as single band multi-spectral image (BMS), PAN image and low-resolution PAN (LRPAN) image. This method work fast and efficient than the other pan-sharpening methods [23]. object-scale adaption scheme is proposed by Wang et at. [22] to fuse the CNN and multi-scale image segmentation method for better outcome. On the whole, Object-Scale Adaptive Convolutional Neural Networks method has great capability to classify the high resolution images with fullest accuracy.

3 Proposed Method

The area selected in our work is the Madurai city, located in Tamilnadu state of India. In population Madurai is the second largest population over 38 districts of Tamilnadu. It is a district headquarters. It is a one of the historical city and also referred as the gateway of south Tamilnadu. Madurai city is known as the Athens of the east. The geographical location of Madurai district North

latitude between 9 50’ 59” and 9 57’ 36” and East latitude between 78 04’ 47”and 78 11’ 23”. The present area of Madurai district is 3710 square kilometres. As per the census of India, Madurai district had a population of about 17.34 lakhs.
The proposed method is performed using MATLAB R2017b. Here we use 1000 samples for training and 500 samples are selected randomly for testing. For LISSIV data acquisition Indian Remote Sensing Satellite P6 version (IRS P6 Satellite) is used. Original LISS IV MS and PAN images of Madurai region is shown in figure 4. For my study some of the selected area is cropped from original PAN and MS image. Cropped LISS IV MS and PAN images shown in figure 1.

Table 1: Original Image Details

Satellite	Sensor	Spatial resolution(m)	Bands with spectral resolution (μm)		Image scale
CARTOSAT-1	PAN_AFT	2.5	--		1:50 000 (approximately)
IRS P6	LISS IV	5.8	Green band	0.52 – 0.59	1:50 000 (approximately)
			Red band	0.62 – 0.68	
			Near Infrared band	0.76 – 0.86	

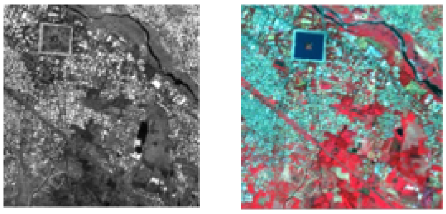

Figure 1: : Cropped PAN and LISSIV MS Images

3.1 Preparation of Ground truth data

in the process of training dataset and also test the performance of classification methods. To determine Land use /Land cover features of Madurai district we perform field visit and collect ground control points (GCPs). Based on field visit and also use e-Trex venture global positioning system device we create reference data set for performance assessment test. The Table 2 shows some of the latitude and longitude of different places visited.

4 Proposed work

The proposed method is used to classify fused PAN and MS high-resolution images using deep convolutional neural network. The flowchart for fusion of PAN and MS image with Classification is shown in Figure 2. In that image fusion performed by four levels using QIM with DCT [11]. After that fused image classified into seven classes of Urban, Vegetation, Wetland, Tank, Water Area, Bare Land, and Roadways by the proposed method of Same Model with Different Training Rounding based on CNN (SMDTR-CNN) .The proposed method is broadly divided into two sections: I. Image Fusion and II. Image Classification

4.1 Image Fusion:

There are three significant portions combined in this section of our proposed work which incorporates pre-processing, wavelet decomposition and best coefficients selection. Wavelet decomposition is

Table 2: Reference point with Latitude and Longitude

Name of the Area	Latitude	Longitude	Elevation (Feet)	Accuracy (Feet)	Features
Burma Colony	9°51’20.5”	78°06’07.1”	148	21	Urban
Sellur tank	9°56’26.4””””	78°07’06.3””””	148	27	Water body
Vaigai river	9°54’45.3””””	78°09’20.1””””	122	23	Water body
Kudhal Nagar tank	9°57’03.9””””	78°06’14.8””””	138	24	Tank
Melamadai	9°55’38.9””””	78°09’06.7””””	135	25	Waste land
Vandiyur stop	9°54’35.3””””	78°09’36.5””””	122	26	Urban
Ring road 1	9°51’23.4””””	78°07’08.5””””	127	22	Road
Chinthamani	9°53’14.8””””	78°08’37.8”	133	26	Urban
Ring road 2	9°51’31.7””””	78°07’15.0””””	125	22	Road
Anna nagar	9°55’04.4”	78°08’55.3”	140	29	Urban
Reserve line	9°56’49.8”	78°07’56.1”	140	26	Urban
Kudhal Nagar	9°57’03.9”	78°06’14.8”	138	24	Vegetation

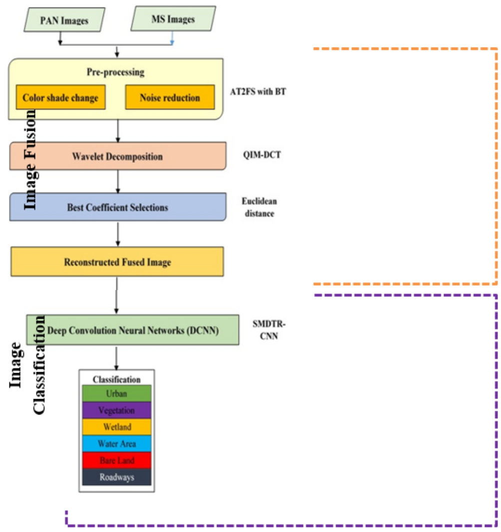

Figure 2: : The Proposed System Architecture

performed utilizing Quantization Index Modulation (QIM) and Discrete Contourlet Transform (DCT).

4.1.1 Pre-processing

The initial step performs by two stages: colour shading change and decrease noise. The principle behind in the pre-processing is to increase the nature of the image information and quality.

4.1.1.1 Color shading change

Image fusion process complexity will be increase using Color image.so we perform color shading change process to improve the performance of image fusion. For example RGB images are made out of three independent color shading of Red, Green and Blue. We use Luminosity method to perform color shading change from RGB image into gray scale image.

4.1.1.2 Noise decrease using A-T2FLS with BT channel

Removing noise from remote sensing image is an essential task to provide better quality input image for image fusion process. Most of the satellite images have noisy pixel values that degrade the efficiency of process. Hence we use Adaptive Type2 Fuzzy System (A-T2FLS) with Bayesian Thresholding (BT) channel filter to remove noisy pixel from gray scale PAN and MS image. Two membership functions such as PMF (Primary Membership Function) and SMF(Secondary Membership Function) are define by a Type-2 Fuzzy Inference System. Based on membership function value pixels are classified good and bad pixels by using Bayesian optimal threshold value.

4.1.2 Wavelet decomposition

We proposed DCT with QIM based wavelet decomposition to decomposed PAN and MS image into five levels. Each image divided into 8 x 8 blocks of window size. DCT-QIM produces sub images of low frequency (approximate original image) and high frequency (detailed original image such as edges, lines, boundaries and region) images. Main purpose of QIM is to provide high PSNR value to reduce error. The DCT of gray image denoted as g(x,y). Each block of m x m image is transfer into frequency domain ge(a,b) by using DCT:

$$g_e(a,b) = \frac{2C(a).C(b)}{n} \sum_{x=0}^{m-1} \sum_{y=0}^{m-1} g(x,y) \cos {}^{(2x+1)v\pi}/_{2n} \times \cos \frac{(2y+1)v\pi}{2n} \tag{1}$$

Where $C(v) = \begin{cases} \frac{1}{\sqrt{2}}, & for\ v = 0, \\ 1, & for\ v = 1, 2, \dots, n-1 \end{cases}$

4.1.3 Best coefficients selection

To fuse high and low frequency sub images we use Euclidean Distance to select best coefficients. Because frequencies with low distance achieve the high priority compare to other coefficients. X and Y are two coefficients then the Euclidean distance is computed by Then inverse Discrete Contourlet

$$D(X,Y) = \sum_{i=1}^{N} (X_i - Y_i)^2 \tag{2}$$

Transform is performed to reconstruct fused image. To improve performance of classification we convert fused image into RGB image The inverse DCT of g(x,y) for g_e (a,b) is defined by,

$$g(x,y) = \sum_{a=0}^{m-1} \sum_{b=0}^{m-1} \begin{matrix} C(a)C(b) \cos \frac{(2x+1)v\pi}{2n} \\ \times \cos \frac{(2y+1)v\pi}{2m} \end{matrix} \tag{3}$$

4.2 Image Classification

So as to characterize the fused image, Deep Convolutional Neural Networks (DCNNs) are suggested which arrange the image into 7 classes: Urban, Wetland, Vegetation, Tank, Bare Land, Water Area, and Roadways. The proposed strategy explores a deep learning based order technique for remote sensing images, especially for fused LISS IV and PAN images with different changes and multi classes. In particular, to help build up the comparing classification strategies, we consider Deep Convolutional Neural Networks (DCNNs): A) Convolutional Neural Network (CNN) B) Same Model with Different Training Rounding dependent on CNN (SMDTR-CNN).

4.2.1 CNN Based Fused Image Classification

The fused (PAN +LISS IV) enhanced image characterization design is dependent on DCNN. The reason for the characterization design is to save neighborhood restraints and concentrate semantic data. Under the thought of the above mentioned, the structured architecture comprises of three sections. The initial segment is the fused image input, and the size of each image is 128X128 pixels, and the quantity of channels is 3. In the subsequent section, to extract features we applied four convolutional layers. The kernel size of convolution layer is n × n × g, where n size is less than 128 and g is less or equal to 3. In the interim, two layers of max-pooling (2 × 2) are embedded into the DCNN layers to decrease the boundaries and keep valuable features. The last part act as image classifier such as fully connected layer to map is a fully completely associated layer for image classification.

1) Feature Extraction

CNN-based feature extraction comprises of three perspectives: convolutional layers, ReLU function layers, and Max pooling layers. In our architecture we use four convolutional layers. There is two different kernel size is 3×3 with a dimension of 128, and 3×3 with a dimension of 64 [24]. To increase the speed of CNN network we use activation function such as ReLU to acquire activation value with the use of threshold. Max pooling is one type of pooling operation used to decrease number of parameters. After convolution layer 2×2 kernel size of max pooling is applied. **2) Classification Scheme**

The completely associated layers are applied to join the features with past edges. In our work, we utilized three completely associated layers with 1024, 512, and 10 neurons separately, to interface with the following convolutional layer. To measure the likeliness of each category acquire by using Softmax model of classification.

3) Loss Function and Regularization

The cross-entropy drop work is the most famous target classification capacity in CNN. It is characterized as in Equation (4): where C is the quantity of classifications, yi is the genuine mark, and h is

$$L_{\text{cross-entropy loss}} = L_{\text{soft max loss}} = -\frac{1}{N}\sum_{i=1}^{N} \log\left(\frac{e^{h y_i}}{\sum_{j=1}^{C} e^{h_j}}\right) \quad (4)$$

with $y_i \in \{1, 2, \ldots., C\}$

$h = (h_1, h_2, \ldots\ldots, h_c)^T$

the last yield of the system.

Dropout is the most generally utilized regularization in CNN, which outfits with the completely associated layer. It decreases the unpredictability of the system, but at the same time is a viable collaborative learning strategy in deep learning models. The guideline of dropout is that the heaviness of the neuron is set to 0 arbitrarily with likelihood p for every neuron in each layer in preparing, and the entirety of the neurons are dynamic with their weight duplicated by (1 - p) to guarantee the loads of the preparation and testing have similar desires.

4.2.2 Same Model with Different Training Rounding based on CNN (SMDTR-CNN)

Two different level of ensemble learning is performed in deep learning method. One is Data level ensemble based on training data set and also process based on unbalanced datasets. Another method is Model Level ensemble. It contains two different type such as single model and multi models. Muti-layer ensemble is one of important single model ensemble method to use by image classification applications. There are four methods available in the multi model ensemble such as voting, simple averaging, stacking and weighted averaging. For best performance we use weighted average method denoted as Same Model with Different Training Rounds (SMDTR) represent in Equation (5), To

$$S = \frac{\sum_{j=1}^{N} w_j s_j}{N} \quad \text{with } w_j \geq 0\,, \quad \sum_{j=1}^{N} w_j = 1 \quad (5)$$

Where s_j denote score and w_j denote weight of the j-th (j=1,2,3) model.

increase the performance of model and also improve accuracy rate of fused image classification we proposed architecture of model ensemble based on CNN (SMDTR-CNN). The proposed SMDTR-CNN architecture is appeared in figure 3. We gather output produced by several model during the training phases, and then performed weighted averaging on chosen models to build another new model for fused image classification.

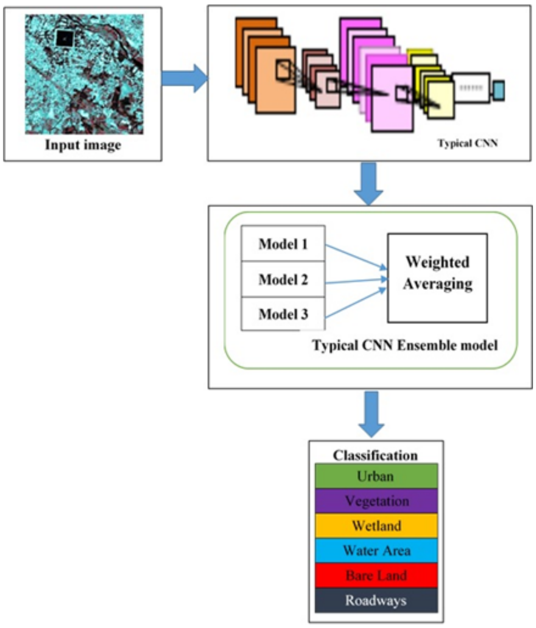

Figure 3: : The architecture of SMDTR-CNN for classification.

5 Experiments

5.1 Experiment Setting

Remote sensing image choice assumes significant job in remote sensing image fusion and classification. An investigation is performed utilizing MATLAB R2017b. the quantity of preparing tests are 1500 and the testing tests are 750. Indian Remote Sensing Satellite P6 rendition (IRS P6 Satellite) is utilized for MS LISS IV information securing. Figure 1 shows unique LISS IV MS from IRS P6 Satellite and PAN image from CARTOSAT-1 Satellite. With the help of Ground Control Points the geometric corrections are made on these images.

5.2 Performance Metrics

Various image fusion and classification evaluation metrics are consider in this section to validate the accuracy. Some assumption are:

- A and B are LISS IV MS and PAN original image
- i,j are the row and column pixel index

5.2.1 Image Fusion Performance Metrics

a) Peak Signal to Noise Ratio (PSNR): It is a proportion of peak signal-to-noise ratio assessed between unique image and the fused image. It is evaluated in decibels. The higher PSNR shows the better quality in image fusion. It is communicated as in Equation (6). **b) Structural Similarity**

$$\text{PSNR}=10 \text{ X } \log_{10} \frac{\text{Peak}^2}{\text{MSE}} \qquad (6)$$

where $Peak^2$ speaks to the greatest conceivable pixel estimation of the image

and MSE alludes to the image mean square mistake

Index Matrix (SSIM): It mirrors the basic closeness between two images. The higher SSIM shows increasingly comparable. It is communicated as in Equation (7). **c) Root Mean Squared Error (RMSE):** It is the proportion of signal blunder by deducting the test signal (reference) and afterward figures the normal vitality of the error signal. It is characterized as in Equation (8). **d) Spatial**

$$\text{SSIM}=\frac{2\mu_A\mu_B+C_1}{\mu_A^2+\mu_B^2+C_2}+\frac{2\sigma_{AB}+C_1}{\sigma_A^2+\sigma_B^2+C_2} \quad (7)$$

where μ_A and μ_B speaks to the mean worth and σAB speaks to the cross co-change and C_1 and C_2 are steady factors.

$$\text{RMSE}=\sqrt{\frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=2}^{N} f_{I_{(i,j)}}-C_{I(i,j)}^{2}} \quad (8)$$

Correlation Coefficient (SCC): It is a proportion of break down spatial relationship between fused image and reference image. For that spatial weight is registered in Equation (9). **e) Image**

$$\text{SCC}=\sum_{i=1}^{n}\sum_{j=1}^{n} R_I-f_I \quad (9)$$

Entropy (IE): It is a proportion of data substance of a fused image. The higher worth speaks to the melded image comprises of rich data substance and fit for exact order as in Equation (10).

5.2.2 Image Classification Performance Metrics

To improve the precision of this analysis, we figured the NDVI from the close infrared and the red channels, and it was utilized as a pointer (NDVI = (NIR - R)/(NIR + R)). The groups of R, G, B, and IR, profundity, just as the hand-created features including NDVI and the relating ground truth are utilized as contributions to prepare the SMDTR-CNN.

The given measurements of F1 score and the worldwide pixel-wise precision of each class are utilized to evaluate the quantitative execution. F1 score is a portrayal of the consonant mean of accuracy and review, and it very well may be determined as follows in Equation (11): Disarray networks per tile or by an aggregated disarray lattice. Simultaneously, the general precision (OA) can be gotten by normalizing the follow from the disarray network.

5.3 Result and Discussion

In this section we present the discussion in two sections: (1) an evaluation of fused image (2) an evaluation of image classification metrics

5.3.1 Image Fusion Accuracy Evaluation

The Comparison using various image fusion assessment metrics is shown in Table 3. Firstly, we demonstrate the comparison results for image fusion with KNN (K-Nearest Neighbor) [26], HCS (Hyperspecherical Colour Sharpening)[27], Wavelet Transform[28], and G-RBF (Gaussian RBF kernel)[29]. In order to improve the quality of image, image fusion is performed on which multiple images such as PAN and MS images are fused to produce the quality image with high spatial and spectral resolution. Figure 4 shows the results of various approaches for image fusion. The proposed QIM+DCT strategy got 55.53 (PSNR), 1.35 (SSIM), 49.65 (RMSE), 0.978 (SCC), and 0.989 (IE) and furthermore we accomplish higher fusion execution of all performance metrics.

5.3.2 Image Classification Accuracy Evaluation

The precision of each class such Urban, Vegetation, Wetland, Tank, Water area, Bare Land, Roadways obtained by the three methods is displayed in Table 4. It shows that the Model Ensemble based on SMDTR-CNN improved the precision. The accuracy of various classification approaches are graphically represented in Figure 5. It demonstrates that the model group dependent on SMDTR-

$$I(E) = -\sum_{i=0}^{L} H_{f_1} \log_2 H_{f_1} \quad (10)$$

$$F_1^i = 2 \text{ X } \frac{\text{precision}_i * \text{recall}_i}{\text{precision}_i + \text{recall}_i} \quad (11)$$

where,

$$\text{precision}_i = \frac{TP_i}{TP_i + FP_i},$$

$$\text{recall}_i = \frac{TP_i}{TP_i + FN_i}$$

Here, TP_i is the quantity of genuine positives for class I, FP_i and FN_i speak to bogus positive and bogus negative, individually. These measurements are figured utilizing the pixel-based

CNN that improved the classification of every class by 2% and 5% when compared with other DCNN methodologies discussed in section 3. Our work demonstrates that it is indicated that two DNN-put together techniques accomplish various exhibitions with respect to various classifications of images. It is conceivable to plan progressively adaptable outfit learning technique to complete the classification task later on work. After that, our best model accomplishes best in class results on the datasets in Table 5. To compare the accuracy of different algorithms, classified output of enhance fused Madurai (LISS IV + PAN) image with PSO+SVM, CNN, and SMDTR-CNN deep learning methods is shown in figure 6. When comparing all the algorithms, SMDTR-CNN deep learning technique has classified the image more accurately. The design arrives at 94.66% by and large and the deep learning outline performs especially well on fused LISS IV+PAN image dataset. The exhibitions of the proposed techniques are assessed regarding exactness, in general precision, and kappa coefficient. The outcomes uncovered that SMDTR-CNN with Deep Learning with directed strainers got the best by and large classification accuracy of 94.66% and kappa coefficient of 0.9433. Likewise improving the accuracy of every class of fused LISS IV+PAN images in the dataset by 2% and 5%, respectively.

6 Conclusion

Remote sensing image classification with the combination of image fusion could be robust, reliable and scalable. In this paper, to assume control over the benefit of image combination for image fusion, a QIM-DCT (Quantization Index Modulation with Discrete Contourlet Transform) based combination approach for request of remote sensing images is proposed. To increase the image combination execution, we evacuate explicit noises using Bayesian channel with Adaptive Type-2 Fuzzy System. After image fusion, we make image classification by Deep Convolution Neural Networks (DCNNs). The exhibitions of the proposed techniques are assessed regarding exactness, in general precision, and kappa coefficient. The results revealed that SMDTR-CNN got the best all things considered order precision as 94.66% and kappa coefficient as 0.9433. From the results, we conclude that our proposed

Table 3: The Comparison using Image Fusion assessment metrics

Image fusion methods	**PSNR**	**SSIM**	**RMSE**	**SCC**	**IE**
KNN	53.50	0.56	56.33	0.854	0.923
HCS	54.23	0.79	61.45	0.578	0.908
Wavelet	54.68	0.80	58.78	0.712	0.951
Gaussian RBF kernel	54. 89	0.92	54.28	0.788	0.964
QIM+DCT method	55.53	1.35	49.65	0.978	0.989

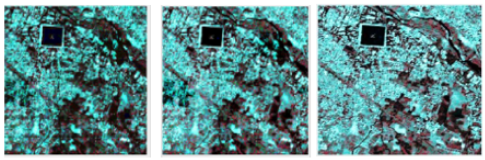

Figure 4: : Figure 4 Result of various Image Fusion Approaches a) Wavelet Transform. b) Gaussian WBF. c) QIM+DCT

Table 4: The classification accuracy (in %) of each category

Category	The precision accuracy (in %) of Algorithms		
	PSO + SVM	CNN	SMDTR-CNN
Urban	96	97	97
Vegetation	91	94	97
Wetland	75	80	84
Tank	57	63	69
Water Area	93	95	96
Bare Land	88	92	94
Roadways	90	92	93

approach outperforms than the previous approaches. In future, we plan to broaden the methodology on other optical remote sensing images rather than using LISS IV just and more classes are foreseen using different classifiers.

Declaration:

Ethics Approval and Consent to Participate: No participation of humans takes place in this implementation process

Human and Animal Rights:

No violation of Human and Animal Rights is involved.

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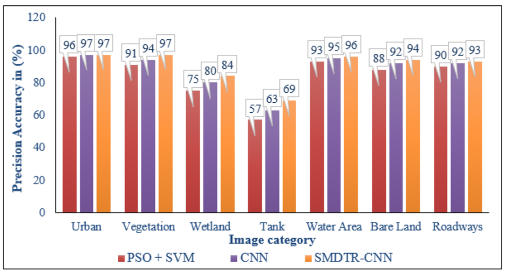

Figure 5: :Figure 5 The classification accuracy (in %) of each category

Table 5: The classification accuracy (in %) of each category

Algorithms	Precision	F1 score	Recall	Overall Accuracy (OA)	Kappa Coefficient
SVM+PSO	0.9323	0.9278	0.9316	0.9306	0.9298
CNN	0.9421	0.9312	0.9342	0.9403	0.9312
SMDTR-CNN	0.9478	0.9352	0.9432	0.9466	0.9433

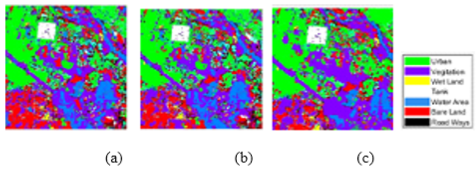

Figure 6: : Result of classification for proposed versus existing approaches a) SVM+PSO b) CNN c) SMDTR-CNN

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