A Process Of Gaining High-Resolution Land Satellite Image By Convolutional Neural Network Approach

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Abstract: An algorithm of satellite image was one of the important topic in the remote sensing field. A deep learning methods in this field such as object detection and classification of image has led to the process to the issues of remote sensing. CNNs are the important deep learning process which used in the classification of image. The use of Convolutional Neural Network in satellite image division was new one. Because of the computational difficulties of three dimension convolutional neural network that aim to remove both spectral and spatial data, two dimension CNNs highlighting on the removal of spatial data were preferred. High resolution images consist of hard spectral data and also spatial data. In this paper, a two and three dimension CNN design using spatial and spectral data was used to remove perfect data from high resolution images. The design was analysed on a worldview 2 satellite picture adding agricultural material like uses of land like roads & buildings, tea and nut groves. An output of the Convolutional Neural Network depend model are correlated against of the RF and SVM algorithms. An accuracy of classification are existed by 900 points produced through web interface developed for the purpose of crowd sourcing. It was 94.7% for the two and three dimension CNN design, 87.9% for the support vector machine and 89.7% for Random Forest.

Keywords: CNN, satellite, resolution, random forest, SVM, spectra, spatial data

1. Introduction

Deep Learning process was enabled through the model of CNN in the last few years. CNN provides some powerful techniques for analysing a different issues in image division and computer vision. An equally and related issue was SI classification which was difficult for delineating and understanding. It comprises the tera bytes of information and important difference because of some rules in filtering, data acquisition and pre-processing. The detecting issues for different covering of lands was a complex issue determining the increasing high class difference in land cover like water bodies, trees, barren and grasslands. Because of the high difference in the SI data, deep NN depend classification process have struggled traditionally to generate a manual process.

It examined an active architecture depend upon convolutional neural networks to study the diversity of intra class and spatial data, attaining the process of state of art. It also examined a structure depend upon networks to attain high perfection in dividing high resolution SI. It also standardized a DSML algorithm with a deployment that aims to decreases the comparison among them. This structure existed state of art outputs in the division of high resolution SI. It also introduced 2 high resolution SI data sets called SAT -4 and SAT-6 and examined a structure which removes the handcrafted characteristics from an input picture and provides the normal characteristic vectors to a DBN for division. Both SAT -4 &6 cover an area of 700 square kilometres at one meter resolution and may be analysed to examine and research the use of different learning designs for high resolution SI division. Both SAT 4 and 6 are tested from a data set, NAIP data set that covers the entire US and may beused to develop labelled maps that may be used for different apps like estimating an area of roof tops for the production of solar power and calculating carbon content in ground.

A spectral and spatial two and three dimension CNN design was analysed in this research for covering land by high resolution SI data. The design of three dimension enables the spectral and spatial uses and remaining two dimension blocks give a powerful deep learning process for spatial features. The design was examined with Deimos 2, IKONOS, Pleiades images to examine the model process on various SI of different areas. An output was compared against the output of the support vector machine and random forest.

2. Literature Survey

Many classifiers for the sensing information are utilized wordly to intellectual data for the aim to classify the activity of earth. A technique of traditional division was possibility depend like Bayesian theory with few expectations. A recent technology was depend upon the neural networks for effective division.

A classifier of neural network has 3 concepts. They are 1) it was self-adaptive information driven with no functional mentioning. 2) it was functional combination. 3) it was non-linearity of the division. Neural network contains parallel network with relation of the many neurons. DNN was referred as the neural networks along with many hidden parameters and layers in the 4 basic machine learning they are RNN – hierarchy was used for processing the input information, RNN – it was modelled to identify sequences along with the memory, CNN – it was a standard network where pictures are identified by many elements and Unconfirmed well-trained networks. It was examined a LFCS which was uncertain rule depend learn valued information and design. This system do not be exercised over the obtained samples. An achievement of task was more difficult in uncertain system because of the dependence on process. A neuro system was a uncertain system by learning algorithm while having sample depend uncertain rules and sets parameters. Hybridization was used to have better process for SI division. Various classifiers are used for the division of the sensing information that adds object depend classifier, supervised and unsupervised classifier. Material and methods

3.1 Study area and data set

Deimos-2, IKONOS and Pleiades images of various areas are divided by the identical design but with different combination in class. IKONOS was existed from the ESA website with the allowance of European space agency. This IKONOS image fits to an urban place in Portugal, porto. This image has one panchromatic band at one meter spatial resolution and four multiple spectral bands at four meter resolution. Land cover areas for IKONOS image are considered as road, buildings, forest, soil, shade and green area. An image of Pleiades with four spectral bands at 0.6 meter spatial data involves to a rural place of Urdu province in Turkey. Land for this image are road, shadow, forest, building, soil and green area. Dms-2 as existed from the European space agency website with the authorization of European Space Agency. This image was in the area of Sierra mountain range in Spain. It cover road, tree, shadow and soil.

3.2 3.2 Land-cover categories and reference data collection:

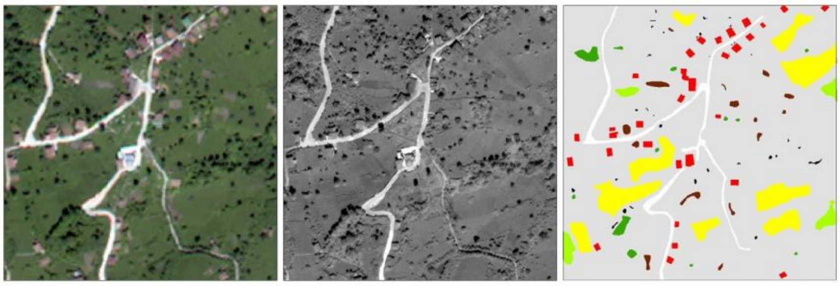

Figure 1. Original WorldView- 2 multispectral image (true-colour), the panchromatic image and the generated reference data set.

Seven LULU classes are found on the WV-2 SI. This was the 1st step. Then the data set for training was developed by the ARCGIS software using the important google earth and image of WV-2 was used for managing the training information collection. This was developed in ARCGIS as polygons showing the borders of the pixel area to denote each and every class. Figure 1 represents the polygon feature.

Training data for IKONOS, Pleiades and Deimos images were generated using these images and panchromatic bands with the selection of pixels representing related classes. As in the WV-2 image, Google earth images were used to check whether the training data representing each class was correctly selected. Table 1 below shows the training data collected for IKONOS, Pleiades and Deimos-2 images of different land cover classes.

Congalton and Green (1999) examined a method depend upon the deployment of multinomial in measuring the reference points needed to produce the matrix for an assessment of post classification. The minimum needed reference was increased and the samples for each division may be considered to the place that it covers on the map. In current years, the spatial determination of SI was reached half meter or improving the needed number of reference points. Both of them also offered the corresponding deployment of multi nomial formula to consider the minimum points needed for an assessment of post-classification.

$$n = \frac{B\pi_i(1-\pi_i)}{b_i^2} \qquad (1)$$

where 'n' denotes the number of minimum reference points needed B ¼ ða=kÞ 100th, 'k' r denotes the classes, a denotes the confidence break 'pi' was the proportion of the area and b represents the needed accuracy. The minimum needed point for deimos-2, IKONOS and Pleiades are identified to be 26, 56 and 124, but 150, 350 and 450 reference points are used for the assessment accuracy of below images.

Table 1. The names, class values, colours and total number of pixels (IKONOS, Pleiades, Deimos-2 Images).

IKONOS			Plaides			Deimos-2		
Class name	Colour	Total number of pixels	Class name	Colour	Total number of pixels	Class name	Colour	Total number of pixels
Forest		2358	Forest		2465	Forest		2620
Grassland		2358	Grassland		3932	Shadow		1172
Shadow		157	Shadow		765	Soil		1691
Soil		2327	Soil		8436	Road		2659
Water		922	Building		5822			
Building		1575	Road		6736			
Road		2360						

SS-CNN model

Many DL procedures are analysed by community of computer vision. It usually deals with the red green blue images. CNN depend networks are modelled to divided three band images. Studies on the issue of meaning division highlights mainly on three band colour and CIR images in sensing data Therefore, a convolutional neural network depend design modelled to analysis the multiple spectral images with three bands to increase the division accuracy.

Any picture having more than one band must be determined as an array of three dimension pixels. Here pixels have identical values to create a feature. Because of the particular nature of convolution neural networks, a process was appeared to identify the matrix to remove the explanatory or relevant characteristics for a local image. A taken multiple spectral picture P required to be disintegrated into LSS overlapping three dimension patches here S denotes the size of the window and L denotes the bands. The number of three dimension patches which can be chosen on P image may be fomulatd as MN=S2:

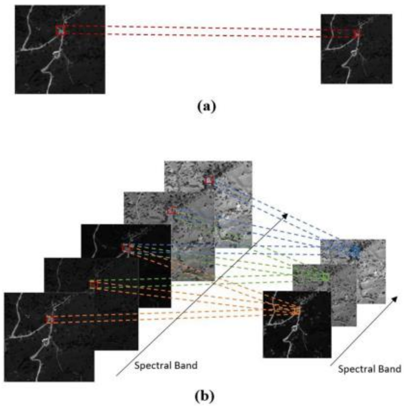

Figure 2. Convolution Types (a) 2D Convolution layer and (b) 3D Convolution layer.

There are three kinds of convolution process in convolution neural network. They are one, two and three dimension. This was shown in the figure 2.The two dimension convolution level rejects the association in slides and adjacent bands. The kernel with columns and rows to move horizontally and vertically to examine the whole 1 band picture, while three dimension convolution was shown in the figure 2b.

One dimension convolution was not analysed in the given SS-Convolution Neural Network design. A data about three and two dimension convolution will be provided. An input picture was tripled by the values of every channel colour and the sum of the values is shown in the two dimension – convolution neural network. After this process, it was analysed on each channel. Two dimension convolution was activated in the given forma of the below formula

$$v_{ij}^{xy} = f\left(b_{ij} + \sum_{p=0}^{P_i-1} \sum_{q=0}^{Q_i-1} \sum_{r=0}^{R_i-1} w_{ijp}^{qr} v_{(i-1)p}^{(x+q)(y+r)}\right) \qquad (2)$$

where i was a particular layer, j was the map i, ðx, yÞ are the keys of the feature map, ðq, rÞ are the keys of the kernel and f is the initiation purpose. vijxy is the result at position ðx, yÞ where v indicates the variable result in the map. bij is the preference limit and p keys over the set of feature maps of the ði 1Þth layer, which are the inputs to the ith layer. w indicates the value of weight parameters, ðP, QÞ represent the size of the kernel and feature maps, respectively.The three dimension convolution was processed by convolving a three dimension information along with a three dimension kernel. Thrre dimension convolution was used in the 1st step in the given spatial and spectral model.

$$v_{ij}^{xyz} = f\left(b_{ij} + \sum_{p=0}^{P_i-1} \sum_{s=0}^{S_{i-1}} \sum_{q=0}^{Q_i-1} \sum_{r=0}^{R_i-1} w_{ijp}^{qr} v_{(i-1)p}^{(x+q)(y+r)(z+s)}\right) \quad (3)$$

The bias and kernel weight are used in the convolutional neural network which was trained generally with a descent gradient technique along with an well-defined approach. Convolutions are used to remove spatial data that was difficult for processing image in predictable 2D convolutional neural network. High resolution spatial images have important amount of spectral data. it has more than 3 spectral bands. It was truth that three dimension convolutional neural network must be preferred to remove both spectral and spatial data from a multiple spectral image, but three dimension convolutional neural network need much amounts of long processing and memory status. The SS convolutional neural network design was examined t analyze the low memory and time processing.

A sigmoid process may generate values in zero and one. The gradient of this process was 0 and very close or near to the zero or one. The neurons gradients generates result values very close to zero or one. This type of neurons was known as saturated neurons. The neurons weight are not updated. The other neurons weight was fixed to these neurons are slowly updated. This issue was called disappearing gradient issues. An activation of tan process generates result values in one and one. The issue of disappearing gradient rises here, large and small values will generate values close to one and one. ReLU was a fast process with low difficulties. It was chosen to generates very correct output. when all the negative valuses are zero, the neurons and weights are not updated. This issue was known as dead neuron issue. It protects counter dissemination.it was given as

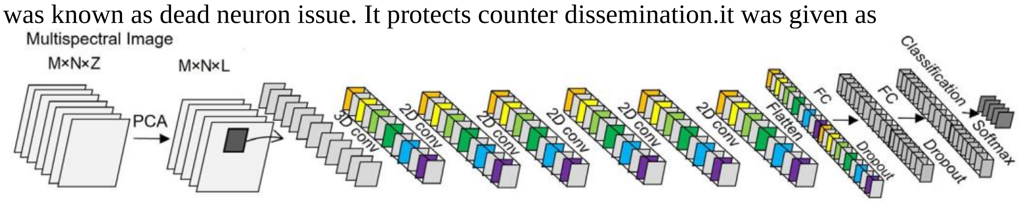

Figure 3. SS-CNN model for high resolution satellite image classification.

$$\text{PReLU}\,(x_i) = \begin{cases} x_{i,} & \text{if } x_i > 0 \\ a_i x_i, & \text{if } x_i \leq 0 \end{cases} \quad (4)$$

where xi was the input on the ith channel and ai was a rate of learning. The rate of learning can be determined as the rate where the gradient parameters acquired in the direction of gradient. New convergence take more time when this proportions was small. When it was large, the design diverges and the severe loss may indefinitely fluctuates.

An initial rate of learning was chosen to be very close to zero and the rate was updated using the method of scaling, based upon the small size of batch and no of iterations. The rate of learning in this research was selected as 0.002.

An algorithm of Adam was chosen as the optimizer till it gives believing process to gain in the speed of training process. This algorithm was famous because it consists many benefits while comparing to other algorithms and may compete with the other methods. This was used as a signal to noise normalization identical to the RMS PROP and ADA grad.

The examined design was a deep framework, two dropout levels are used before the whole associated level to protect the speed and over fitting up the process of training. It the framework was adapted fully to training information, it can loss its capability to produce. This was seen as a issue of over fitting in NN. A large no. of weight measurements are processed to analyzee convolutional neural network. Over fitting can occur when there are some samples for training.

A ratio of two dropout levels is chosen as 35% and 25% to generate the outputs from the produced network framework. An examined SS-CNN design was shown in the Fig 3. In the [3.3.3] process where there is I spectral dimension and 2 spatial dimensions. The 3_D of the slid filter for all the three locations, which is the width, ht, and no.of bands. At each stage the element level addition and multiplication will add up to 1 number. This is due to the reason that filter may slide down due to the shape of 3-D. the outcome are placed in the space for 3-D in order to form a dataset of three-dimensional.

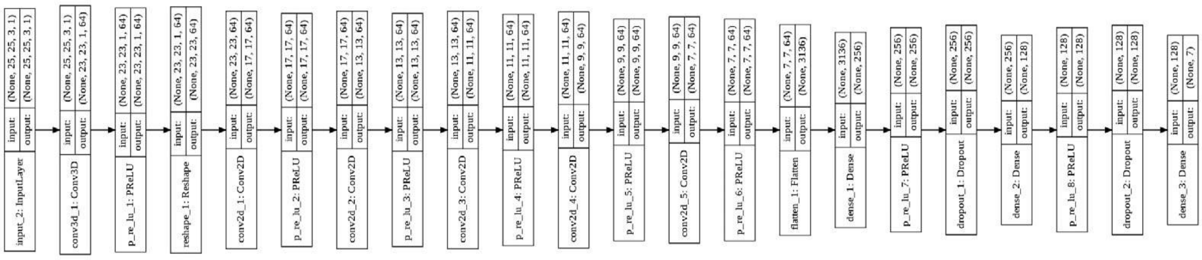

Figure 4. Summary of SU-CNN based model.

The proposed is also having 5 two dimensional Convolutional layer. The Dimension of the 1st 2-D layer is represented as (63,5,5,63) where the 63 is the Kernel Number, and the 5 is the Spatial-D of the 2-D kernel and the other 64 is the no.of 2-D feature map. The 63 number on the left side indicates the filter with size of 5x5 which has been utilized. the feature map for the convolutional layer is made using the calculated values from the corresponding position to the kernel centre position. With the usage of 63 filter, even the output will also be 63, which is the represented in the rightside. The remaining dimenson of the 2-D convolutional layers are represented as [62,4,4,62], [62,3,3,62],[64,3,3,62] and [62,3,3,62]. Fig 4 gives the detail explaination of the types of layer, its size of output, and other parameters utilized in the model.

Fig 4 shows the number of class in the World-View-2nd –image was found to be seven. It is represented in the output of the 3rd dense layer. The overall parameters was found to be 1.322.245. this was obatained by measuring all the parameter value in all the layer. In the input layer the number of parameter was found to be zero. This is due to the input layer's biased decision using the filter and output feature map dimensions. The ConV2-D filter size was found to be [7:7]

The output and input property of this layer was found to be 64. The number of calculated parameter was found to be 7 7 64 64 þ 1 64 ¼ 200768. The parameter numbers is given with the help pf no.of feature map and product of the feature map. The feature map size of the model was found to be [22,22] and the no.of features was found to be 64. The parameter value is obtained by adding the bias product to the input as well as the output.

The adam Optimizer is used for training the model with the help of the algorithm based on propogation through a Softmax Loss/Cross Entropy Loss function.

Here, the input vector is Xi and the corresponding categorical vector is Yi:

$$L(X_iY_i) = -\sum_{j=1}^{c} y_{ij} * \log\left(p_{ij}\right) \quad (5)$$

Y_i categorical vector $(y_{i1}, y_{i2}y_{i3} \dots y_{ic})$;

$$y_{ij} = \begin{cases} 1 \text{ If i.element is in } j - \text{ class} \\ \quad\quad 0 \text{ if not} \end{cases} \quad (7)$$

$$P_{ij} = f(X_i) \quad (8)$$

Mini-patches of size 256 were used and the network was trained for 100 epochs.

4. Results and discussion

4.1 Classification results of WV-2 image

The SU-CNN model success maily relies on the outcome of the comparsion made with the two dimensional process of the conventional neural network. this model is developed using the Keras through TensorFlow with Google Colab implementation the backend. In the classiifcation process odf the CNN where the no.of kernels, kernel size, depth and the window size is given more importance.

The size of the window was found to be 13,13,24,24,26,26, and 28 and 28. This window is tested with the window size of 25x25 model size of the window was made default becaue with this size only better performance is achieved. At the point when the quantity of convolution channels is expanded excessively, the preparation time and the quantity of boundaries to be determined increment significantly. In this manner, the channel numbers were chosen as 64 for each layer in the model. The dimension of the filter was found to be 2,2,2,3,4,6,6,7 through which the geometry of the building can be determined. When all the filters are chosen then the 3x3 D of the road boundry may be deteriorated and the training time and the parameter of the time will be increased. With the usage of 7x7 filter will surely lead to a failure to the fine detailing. The filter's size is shown in fig 4 where the speed of the model will be increased, the data size will be reduced to a certain level based on the PCA model.

The accuracy and the speed of the model and the experiment of the model is used to find the optimum dimension of the PCA algorithm for feature selection. The standard size of the dimension was fixed as three and the depth of the 3-D Convolutional layer was shown as three in the model. The traing process for all the test was done at the spped of the 30 epochs. The Average Accurcy (A), Kappa Coefficient (K), OA is the overall Accuracy is used for post-classifcation for the assement of accuracy. 10%, 20% and 70% are the data assigned on a random basis for the testing, validation, training purpose. The following table 2 indicates the accuracy of classification of the 2-D of the CNN and the SU-CNN process.

Table 2. Accuracies of CNN models.

	Accuracy		
	(%)OA	(%)AA	(%)K
2DCNN	92.3	91.8	92.0
SS-CNN $(3D-2D)$	95.6	94.8	95.3

Fig 5 describes the 2-D of the CNN model where the miscalculation occurred in the building image's pixel on the road boundary. At the same time, misclassification was also found in the region where the image labelled for road boundary was supposed not to be position of labelling. In the SU-CNN model the mentioned errors are slight low in the outcome process.

The SVM and Random Forest classification is done usihng the similar system. In the 3-set of classification process the similar sampling was set which is indicated in table 3. The SVM classification was done using the [Environment for Visualizing Images] ENVI. In the ENVI the penalty parameter, the pyramid level, the gamma value, kernel type, and the threshold tupe are used for SVM classiifcation. [17] proper guidance will help in selecting the correct kernel with specific parameter. RBF [Radial Basis Function] was utilized for kernel process. This is used for many when compared to the other methods.

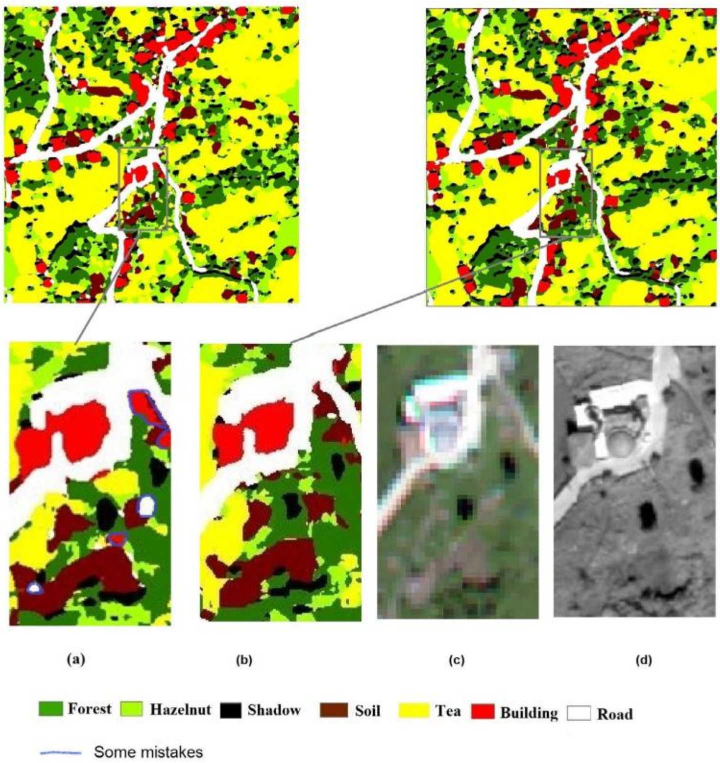

Figure 5. (a) 2D CNN, SU-CNN, (c) Worldview-2 True-colour, (d) Worldview-2 panchromatic band.

The user can also set the parameters of ENVI. Where the gamma value will be more or equal to 0.01.

The penalty parameter can adjust the value of the balanvce between the forcing rigid margin where the classification was set at zero. Through which the image can classified based on original resolution value. And also the 0-thresold can be used for making that all the pixel of the image can be set for any one of the class. Table 3 indicates the 7th class classification process.

Table 3. The names, class values, colours and total number of pixels (WV-2 Image).

Class name	Class value	Colour	Total number of pixels
Forest	1		4701
Hazelnut	2		7609
Shadow	3		1326
Soil	4		4832
Tea	50292		
Building	6		10978
Road	7		17264

In the random forest classificastion, the imageRandom Forest is used. The number of values in the DT was set to th minimum of 1000 where the error can be generalized and the it will not increase the time of classiifcation. Table 3 describes the sample number and class value and the fig 6 shows the result for the classification process.

In the fig 6 one could see the pepper and salt impact in the RF and SVM , but RF method performs slightly better. In the SU-CNN model, there was not nay trace of any pepper and salt effect due to CNN's intrinsic structure. The subtleties, which are hard to separate from different classes like the street, can likewise be removed effectively and shown unmistakably on the picture. . Notwithstanding the visual assessment, 800 control focuses were arbitrarily circulated on the picture for precision evaluation. The very same 800 control focuses made accessible to various clients to ascertain three order exactness esteems for the 3-models.

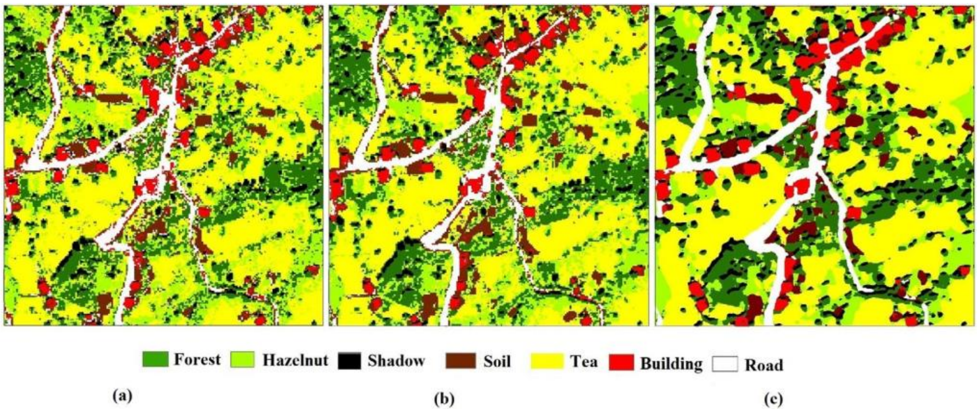

Figure 6. Classification results (a) SVM, (b) RF and (c) SU-CNN model.

Clients were approached to enter the necessary class an incentive for each reference point. A publicly supporting web interface was made in our past investigation (11) for post post-order.

Order precision evaluation is by and large performed utilizing the determined generally accuracy of classification, Kappa, and the confusion matrix. The disarray framework contains the genuine surface pixel arrangement results, with which the picture order results are thought about. The general order exactness is the proportion of the right number of pixels to the complete number of pixels. In Table 4, kappa esteems and in general exactness esteems are given for SU-CNN, Random Forest, and SVM.

Table 4. Calculated kappa and overall accuracy values for 3 classification methods in WV-2 Image.

	SVM	RF	SS-CNN
Kappa	0.8277	0.8640	0.9442
Overall Acc. (%)	86.4	89.2	95.6

The accuracy for the classification model for the Random Forest, the SVM, and the proposed SU-CNN was found to be 85.6%, 88.5%, and 95.6%. While comparing the terms the values of the SVM, Kappa Coefficient, Random Forest, and SU-CNN was 82.2%, 86,4%,and 92.4%. the proposed SU-CNN model yields better performance for all the set of classification accuracy and the Kappa value.

4.2 Classification results of additional image data

The SU-CNN results of classification for the Pleiades, IKONOS, and Deimos-2 were also compared to that of the Random Forest and the SVM model using World-View-2-Image. The IKOMOS results is indicated in the following fig 7.

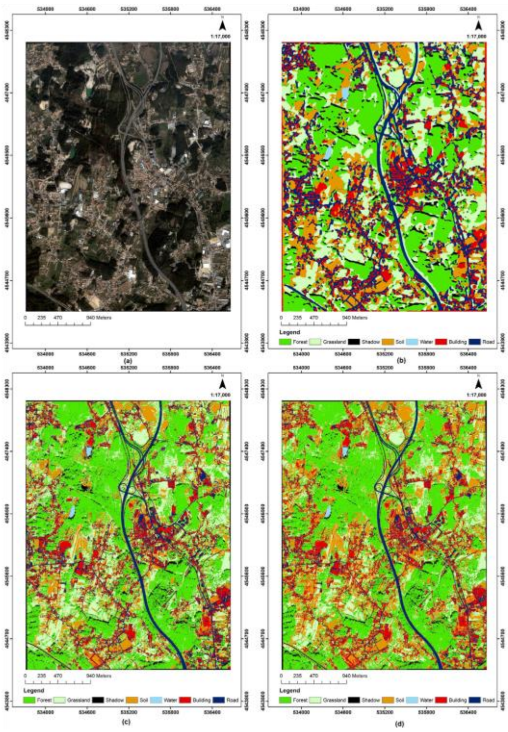

Figure 7. IKONOS Classification results: (a) IKONOS MS Image, (b) SVM, (c) RF and (d) SU-CNN.

Table 5. Accuracy assessment results of additional test data.

IKO NO S					Plaide s	K		Dei mo s-2	
	O A	A A	K		OA AA			OA AA	K
SV M	7 8.5 1	7 4.0 2	7 3.0 9	SV M	76.387 9.01	6 9.3 4	SV M	78. 29 74. 25	6 6.1 6
RF	7 8.1 2	7 2.3 1	7 1.7 2	RF	73.867 3.21	6 5.4 4	RF	81. 58 83. 44	7 1.4 9
SU CN N	8 7.5 0	8 6.0 1	8 4.5 7	SU CN N	87.938 9.31	8 3.9 9	SU CN N	94. 08 95. 69	9 1.1 5

The IKONOS picture has lower Spatial and Spectural resolution than WV-2. Also, as the investigation territory contains a thick metropolitan climate, it turns out to be more hard to recognize the subtleties, making it a troublesome characterization issue. As demonstrated in Figure 7 and Table 5, despite the fact that RF and SVM calculations show effective characterization results, a few pixels that ought to have a place with Building class were misclassified as street. In the SU-CNN model, classes have all the earmarks of being more incorporated. OA esteems for this picture were gotten as 73.51%, 73.12% and 82.50% for RF, SVM, and SU-CNN.

Fig 8 indicates the Pleiades image classification result. This image has 4 –spectral band. But the spatial resolution was found to be 0.6 m. from which it is clear that this process is having significant spatial resolution with less spectural resolution that the WV-image-2.

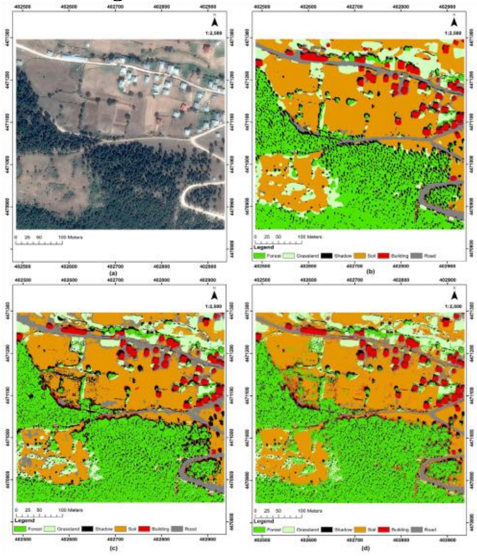

Figure 8. Pleiades classification results: (a) Pleiades MS Image, (b) SVM, (c) RF and (d) SU-CNN.

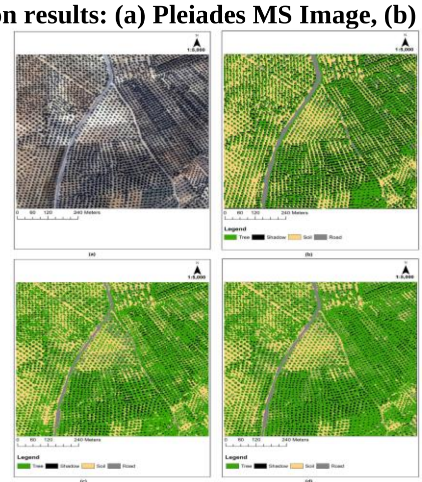

Figure 9. Deimos-2 classification results: (a) Deimos-2 MS Image, (b) SVM, (c) RF and (d) SU-CNN.

The way that the structures are isolated from one another in the test region is useful, yet it is unwanted that the shade of the streets is near the dirt class. As demonstrated in Table 5, SVM has accomplished a marginally more accurate classification result than RF for the Pleiades picture. SU-CNN is by all accounts significantly more effective than the other two techniques since OA exactness for the Pleiades picture is 72.38, 74.86 and 86.93 for RF, SVM, and SU-CNN, individually.

Deimos-2 picture has 4 bands of spectral resolution and its spatial resolution was found to be is 0.85m. The examination region contains less land cover classes than other test pictures. Also, there is a solitary tree structure rather than a woods class. The trouble in the picture is that the solid trees have shading tones like the dirt class underneath them. At the point when Figure 9 is analyzed, it is seen that the SU-CNN structure eliminates the tree tissue better. Besides, even the shadows of the trees showed up in their right positions. It is seen that the SU-CNN structure recognizes the tree surface better. Also, even the shadows of the trees showed up in their right positions.

The performance of the classification model is done by considering all the factors such as the AA, K-metrics, and OA. It is clear that the SU-CNN has the highest value when compared to the other three images. The RF and the SVM model shows same result. It was found that the SVM was more significant in the Pleiades image and the Random forest was a significant in the Deimos Image.

5. Conclusion

This paper has proposed a SU-CNN based is utilized for solving the problem of the Multi-spectral image classification. While the process of obtaining the class for the pixels the utilized type of spectral and spatial information has more accuracy in prediction. Where a 3-D and a 2-D based model is combined for getting the information from the LU-LU sematic segmentation for the Hi-Res of the multi-spectral image. Outcomes from the present model is made for a comparsion on the pixel based Random Forest and the SVM algorithm, through which it is clear that the past studies have provided significant outcome for the High-Res multi-spectral classiifcation. From the outcome of the comparsion result it is clear that the proposed SU-CNN is having more significant performance than the RF and SVM. The SU-CNN was also tested using Pleiades, IKONOS, and Deimos-2-image for various regions which is having different class. The SU-CNN has the accuracy level of 95.6% than the other images especially against the RF and the SVM.

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