A Comprehensive Study on Classification of Hyperspectral Imagery Using Machine Learning and Deep Learning Techniques

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Abstract: One of the major challenges in automated road and building extraction in Indian earth space is the lack of information on highway projects and smart city development, specifically in urban and rural areas. It can be an excellent solution to upgrade road networks and buildings by using hyperspectral remote sensing images. Furthermore, the exact identification and retrieval of road and building footprints with high accuracy is possible when we use hyperspectral imagery. At the same time, the processing time will increase. The aerial photography and multispectral images quickly detect the streets, buildings, and other objects but the accuracy will be less when we compare with hyperspectral imagery. Because the hyperspectral have continuous spectral bands and standard clustered (spaced) spectral bands. To address these challenges,this paper presents a comparative analysis for automated building footprint extraction and road detection from hyperspectral images using machine learning and deep learning techniques. In this research to get high accuracy and reduced complexity machine learning and deep learning techniques are used in hyperspectral imagery. The FCN, SVM, and CNN classification techniques have yield better classification accuracy the process of automated building and road detection has been implemented with machine learning and deep learning methods yield improved accuracy.

Keywords: Hyperspectral imagery classification, Fully convolutional network, Support Vector Machine, Convolutional neural network.

1. Introduction

Remote imaging spectrometry is an ecological and geological research which has a professional role in the classification of spectral elements **(Lange.J et al.,2018)**. The electromagnetic energy extraction from the earth's surface, as well as variation temporal on earth science, are examples of general methods for remote sensing application domains **(Krizheysky.A et al.,2012)**. Using components of classification is important and also improved the feature space of optical image techniques which operates within a visible range is called as hyperspectral imagery **(Chen.Y et al.,2016)**. The absolute data-based topic is discussed before the hyperspectral image analysis and common task is radiometric measurement, according to the spectral response with a narrow bandwidth **(Lakshminarayanan.K et al.,2020)**. The hyperspectral imagery classification techniques implement with various spectral bands and large number of features. Hyperspectral image-based research is difficult process to combination of spectral and spatial parameters**(Li.Q et al.,2013)**.

Hyperspectral image-based road and building extraction has been extensively explored in remote sensing communities with the advent of high spatial resolution hyperspectral sensors and ubiquitous geospatial applications, road detection, and building footprint extraction continues to be an active research topic. **(Veera Senthil Kumar.G etal.,2017)**presented firefly algorithm (FA) and Support Vector Machine (SVM), these Firefly algorithm offers superior results for better classification in the selection of bands but Study on building and road is not done. **(Xie.Fet al.,2018)** proposed Gray wolf optimizer. This Gray wolf optimizer (GWO) ensures strong classification efficiency of the selection band combination, butIt provides poor classification results because the resulting band combinations have a lot of redundancy which leads to a decline in classification performance. **(Nagasubramanian.K etal 2018)**Utilized genetic algorithms and support vector machines. It gives a higher classification of accuracy is 97% better than the visible wavelength. **(Sawant.S.S.& Manoharan P 2020)** Approached Three-Dimensional Discrete Cosine Transform (3D DCT) and weighted entropy-based information. This approach provides highly insightful similarly classify bands compared with the unsupervised range of bands, but Not concentrated on the unsupervised hyperspectral bands. In this paper, comparing to machine learning and deep learning methods for classification from hyperspectral imagery, such as support vector machine, fully convolutional neural network, and convolutional neural network.

2. Dimensionality Reduction

S:No	Author &Year	Methods/Algorithm	Inferences
1	**(Zang.Z., & Mo. D. 2012).**	ICA & PCA Algorithm	Adv: PCA was better performing from the machine operating coast. Dis Adv: But the ICA's performance had not been better than PCA's stability.
2	**(Kolluru.Petal.,2014).**	Support Vector Machine (SVM)	Adv: Using SVM the dimensionality and classification accuracy gets high level (64.70%) Dis Adv: Need to improve the accuracy for further plan.
3	**(Su.Jetal.,2017).**	PCA and SVM	Adv: It performs best with a small amount of training data. Dis Adv: Need to improve the efficiency a hybrid method (feature selection &extraction)
4	**(Dong.Yetal.,2017).**	Ensemble Discriminative Local Metric Learning (EDLML)	Adv: It provides superior classification efficiency with less standard dimensionality reduction. Dis Adv: Need to improve the process of optimization and develop a more weight system to classify.
5	**(Haut.J.M. et al.,2018).**	Extreme learning machine (ELM)	Adv: This method helps to classify high-dimensional images using the real-time application. Dis Adv: When implementing the large data, the processing time increases so need to reduce the time processes.

3. Classification of Machine learning and deep learning

S:No	Author's &Years	Methods/Algorithm	Inferences
1	**(Zhong.Yetal.,2006).**	Unsupervisedartificial immune classifier (UAIC)	Adv: It shows the best result of high accuracy of the UAIC Classification when compare with K-means, ISODATA, fuzzy. Dis Adv: Need to improve classifier by considering the selection or extraction of features.
2	**(Wang.Cetal.,2015).**	Semi-supervised method.	Adv: It indicates the overall classification of the method has high precision. Dis Adv: It's taken a long running time. Focus to apply optimizing method for saving time.
3	**(Makantasis.Ketal., 2015).**	Convolutional Neural Network (CNN)	Adv: This method shows the great potential of the man-made detection system of objects compares to the SVM method. Dis Adv: Plan to frame for hyperspectral video sequence identification of human

			activity.
4	**(Guo.Zetal.,2016).**	convolutional neural networks (CNN)	Adv: When compare to AdaBoost and another technique, the CNN produces an overall accuracy 96%. Dis Adv: The presented design to apply for another high-resolution image for detection road and agricultural land.
5	**(Mou.Letal.,2017).**	Recurrent Neural Network (RNN),	Adv: The RNN shows statistically higher accuracy than SVM, RBN, and CNN. Dis Adv: The same method plan to apply for hyperspectral change detection
6	**(Thanh Noi.P&Kappas.M2018)**	SVM, KNN, and random forest.	Adv: All results of the classification showed high accuracy 90% to 95%. Dis Adv: Further, improve the classification accuracy.
7	**(Nahhas.F.Hetal.,2018).**	Light detection and ranging (LiDAR) data and orthophotos are combined to create deep learning (DL)	Adv: presented model achieved the best working area accuracy 86.19% and test area 81.86% Dis Adv: But did not used a hyperspectral image (high-resolution data)
8	**(Shrestha.S&Vanneschi.L2018).**	Deep convolutional neural networks (DCNN), fully convolutional network (FCN), conditional random fields (CRFs)	Adv: The proposed DCNN-FCN-CRF's outperform both the original and other variants of the aerial image. Dis Adv: Plan to develop the best technique for building extraction can be surveyed and compare to post-processing methods.
9	**(Li.Xetal.,2018).**	Two-stage Subspace Projection (TwoSP)	Adv: This method of experimental reports on two real-world Hyperspectral data (HD) shows successful classification. Dis Adv: Decided to expand the approach for improving the classification and dimensionality quality.
10	**(Hasan.Metal.,2019).**	CNN, SVM	Adv: CNN, SVM given best accuracy of classification of 99%. Dis Adv: To boost the classification efficiency using deep learning methods.
11	**(Guo.Yetal.,2019).**	PCA, SVM Radial Basis Functions are a type of base function.	Adv: When compared to other kernels, SVM with the Radial basis function (RBF) kernel provides better classification accuracy. Dis Adv: The computational time of classification can be further reduced by using a supervised dimensional reduction

			method.
12	**(Zhang.Yetal.,2019).**	KELM (kernel-based extreme learning machine)	Adv: KELM used to performHSI dataset classification process, which can greatly increase classification performance. Dis Adv: In order to take spatial information from different viewpoints from the various successful HIS spectral-spatial models.
13	**(Zhang.Cetal.,2020).**	deep quadruplet network (DQN)	Adv: It provides the highest contribution and classification with time consumption compared to existing methods. Dis Adv: Feature a sample-synthesis method can be explored to the hyperspectral image.

4. Hyperspectral Imaging: Deep Analysis of Road detection

In terms of the number of fatalities (deaths), injuries, and their impacts for users in environment, road traffic accidents are being significant in India. The main problems of road traffic are continually growing, raising a public health issue, and death injury are one of the leading causes of death worldwide, killing over 1.35 million people, with 90% of these deaths occurring in developing countries and 11% of these deaths occurring in India alone. The result of road crashes, every year more than 1.25 million people die, its reported by world health organization. In traffic accidents, the many people killed only lower than 9th-place hepatitis (1.40 million). More than 3,400 people die every day on the road of the world and every year tens of millions of people suffer accidents or disabilities**(Road Accidents in India 2018)**.

In India, in a road crash, 1.47.913 people were killed in 2017. According to MORTH (Ministry of Road Transport and Highways), during the year 2017 Tamil Nadu is the leading state in road accidents and has an accidental death of 16,157 (Road Accident Analysis in Tamil Nadu 2019).In view of a rapidly changing situation, it also considers international traffic connection to COVID-19 outbreak. The general director of the world health organization declared a current outbreak of COVID-19 public health emergency, as well as international road traffic and maintenance issued on 30 January 2020, following the advice of emergency committee constituted under the international health regulations (2005). The result of traffic accidents, and responsible sectors is increasingly being challenged in terms of road quality and road extraction**(World Health Organization WHO Regional Websites 2020)**.

Road network maintenance is important for fast traffic movement. Timely and appropriate road maintenance reduces coastal construction. Extraction of the road network from remotely sensed imagery was systematically investigated for a longer period. The researchers' curiosity is motivated primarily by their possible significant applications. Roads represent a class of high-value objects captured by an image sensor in space. Since several tools are available to detect or identify road safety issues, comprehensive road accident analysis remains one of the major measures of system vulnerabilities. The road safety decision-making process is based on variables that accurately state the level of safety of the modules of a particular road system.

When there is a need to improve road safety or road traffic control, the road features first need to be extracted or detected, and then a road safety access solution developed. For this purpose, traffic management, urban planning, road surveillance, navigation, and map updating have a major significance for research on road extraction. However, the identification of a road object faces various challenges. The material, width, direction, and topology of the road pavement vary over a point. Completely or partially variations created by nearby buildings, trees, and the shadows they create, make it difficult to preserve road connectivity. With the growing use of oblique imagery from aerial and satellite platforms, the problems presented by occlusions are increased. Also, common structures such as roofs and parking areas are constructed from materials that are similar or equivalent to paths.

Image classification methods, despite their great potential for extracting information, some challenges such as the generation of multiple modules of data, that can perform some limited classification task's. Traditional techniques of multispectral recognition of patterns for remotely sensed imaging are based on similar statistics like maximum probability **(Petropoulos.G.P et al.,2012)**. These hyperspectral imaging results are ineffective, since they have a limited capacity to implement the complexity classes, especially classes with sub-classes.Using machine learning techniques to extract the important information from hyperspectral imagery. Hyperspectral imagery using the most common classification techniques, such as SVM and ANN is having considerable time limit, particularly the large database of the training stage. To address these issues, some changes have been developed, without kernel mapping to include LASVM and SVM. The case of overlaps class, first limited binary classification, the second greatly reduces a rate of accuracy. Implemented a model classifier literature method is called as machine learning and deep learning. In this paper, present machine learning and deep learning methods to extracting the geometric road features from hyperspectral imagery improve to impact of comparison between SVM, FCN, and CNN.

5. Hyperspectral Imaging: Deep Analysis of Building Extraction

As the world, second largest region, India accounts for 6% of the world's total primary energy supply. There would be significant consequences for energy use and resulting carbon emission due to rapid urbanization and the increasing urban population. There are many complex interconnected challenges facing cities across various sectors (building environment, public service,etc.,) and it is important to address these challenges by incorporating smart city management concepts to achieve sustainable and low-carbon urban growth. The extraction of urban building footprint is one of the most challenging tasks and, with the evolution and transformation of urban areas into smart cities, smart energy management was also becoming an important part of this urban development.

Prime Minister Narendra Modi of India declared the successful 100 Smart cities mission in 2015, with a roadmap that discussed equality and enhanced people's quality of life. According to government estimates, this, along with other city building footprint extraction initiatives, will help transform India's construction sector into a USD 1 trillion industry by 2015, and it will become the largest employer by 2020 **(Praharaj.S et al.,2018)**. So, developing smart city purpose building footprint extraction is a necessary part of the urban area. A term used to define the boundaries of a building or structure's exterior walls when positioned on a piece of land. The edges of the roof or protected area of the roof framework may also be defined if no walls are surrounding a structure or building.

Automatic extraction of building footprints from satellite images has always been a difficult task due to a variety of factors such as varying building structure, size, color, image resolution or the presence of roadblocks raised by surrounding objects such as tress, roof tops, and so on. The comparison between the building rooftops and background can causes the segmentation problem. Automated building extraction has found applications in a variety of fields, including land use and land cover analysis, change detection, urban planning, disaster management, and many other socio-economic activities. Remote sensing and GIS technology are essential in these applications. The development of sub-meter frequency resolution from high-resolution earth satellite like IKONOS, World-View, and QUICKBIRD, on the other hand, has greatly expanded remote sensing possible applications. Most of the approaches still using LiDAR data to achieve better performance, but LiDAR data is typically more expansive and then less satellite data image is available. HRS imagery helps in the detection of various urban-related features on the earth's surface, such as buildings, roads, trees, and other natural and man-made objects **(Gavankar.N.L&Ghosh.S.K 2018) (Chawda.C et al.,2018).**

In this paper, proposes extract buildings footprint and road detection in urban environment from hyperspectral imagery. The classification approachesare support vector machine, a fully convolutional network, and convolutional neural network. Pre-processing methods are used to get the standard range of intensity values. Finally, to improve classification, SVM and CNN techniques have been implemented for high classification accuracy in different areas such as building footprint extraction and road detection from hyperspectral imagery.

6. Proposed Methodology

The proposed architecture methods of comparative analysisare shown in figure 1. Preprocessing will be used for the hyperspectral imagery, as well as geometric transformation tool and dimensionality reduction methods. Based on geometric knowledge the buildings and road segments will be together. A polygons segmentation method is used to detect the buildings edges. For road and building footprint classification will be used CNN, FCN and, SVM. This paper used three levels of datasets like Pavia University, Washington DC Mall, and the United States of hyperspectral imagery.

The research flow represents the comparison proposed framework for road detection and building footprint extraction. It is divided into different phases. The first stage is designed for hyperspectral data preprocessing using a Gaussian filter and geometric transformation tool. The second phase is the reduction of the dimensionality like a reduction of the spectral data using the main PCA and ICA techniques and convert polygons segmentation. Finally, the selected band is to apply to the classification part to find the automated building footprint extraction using the hyperspectral image with deep learning methods of the fully convolutional network (FCN), Convolutional Neural Network (CNN), and Support vector machine (SVM) which helps to extracts the building boundary and road detection.

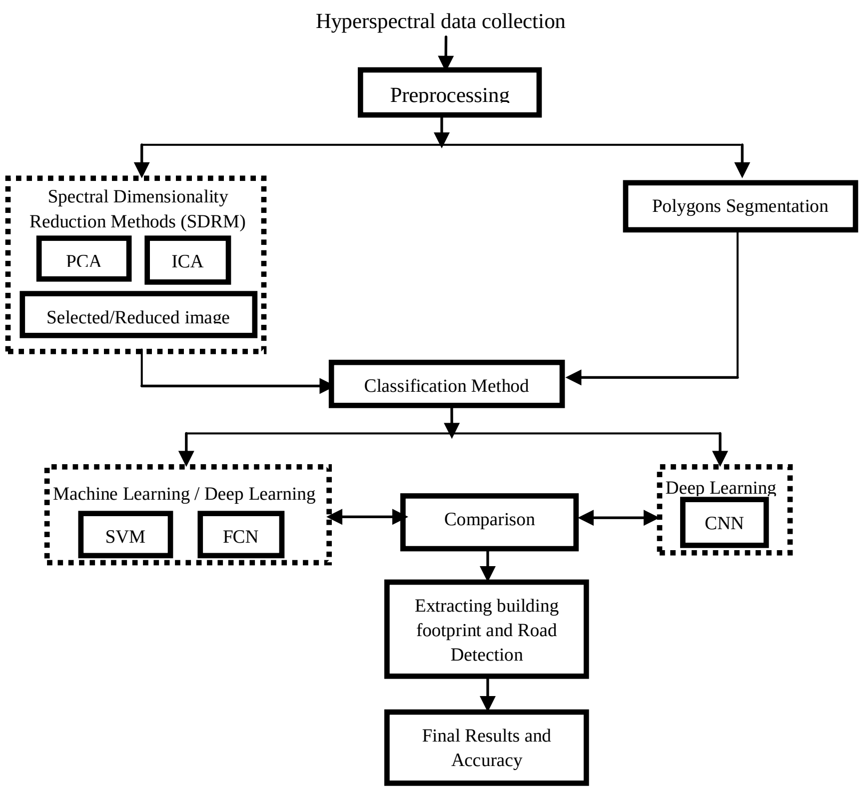


Fig 1: Flowchart of the proposed work for comparison

6.1. Classification Methods

Classification is a great tool for evaluating the various land cover from hyperspectral imagery (HSIs). In the area of remote sensing, the HSIs classifications have been a well-established research subject, and the curse of dimensionality reduction is inherent primary challenges. The fundamental aim of hyperspectral image classification, for each pixel of class labels, is to assign the given set of class labels to observation. The purpose of the classification of the hyperspectral image is to identify between each pixel's land-covered forms, which also have hundreds of spectral bands. In this paper, compared major developments in hyperspectral image classification in terms of CNN, FCN, and SVM.

6.2. Fully Convolutional Network (FCN)

Proposed a novel approach based on deep learning which utilizes fully convolutional network layers (FCN) to allow greater stability hyperspectral data for spectral and spatial information. The natural images from hyperspectral classification, the FCN model has achieved state-of-the-art result. To convert images pixels into pixel categories, a fully convolutional network (FCN) used to convert width and height of the feature map of intermediate layer.The size of the FCN input images is modified through back convolutional layer.So, the input of spatial dimension is predicting the correspondence of one-to-one dimensions **(Vapnik.V.N 1998).**

6.3. Support Vector Machine (SVM)

A linear Support vector machine classifier was used for this task (SVM). The SVM is mainly used for monitoring training in task such as classification and regression issues. The SVM can identify the nearest feature of the vector points, because the memory efficient have best work in the classes of challenges. The next process of the algorithm to finding points is to draw a line between the last positions then find out where the two categories are found the initial connection system. The separation of the two developed classes is found using the existing drawn line. A linear kernel is a similarity result which produces good outcomes as non-linear or multilinear kernels. When SVM implemented the linear classifiers, it performs better than other function of face recognition and handwritten classification methods. After the proposed method has extracted all the features in the image and each image is given a label of +1 or -1 to represent the outcome.

6.4. Convolutional Neural Networks (CNN)

Convolutional Neural Network models is a strongest deep neural networks hierarchy with hidden layers between the overall system layers, such that structure weights can learn more about the functions found in the input image. Various types of layers are creating a basic CNN architecture. The convolutional layer produces the output feature map by applying an array weights to all the input parts from the hyperspectral image. The information provided in the efficiency of the convolutional layer is simplified by the pooling layers.

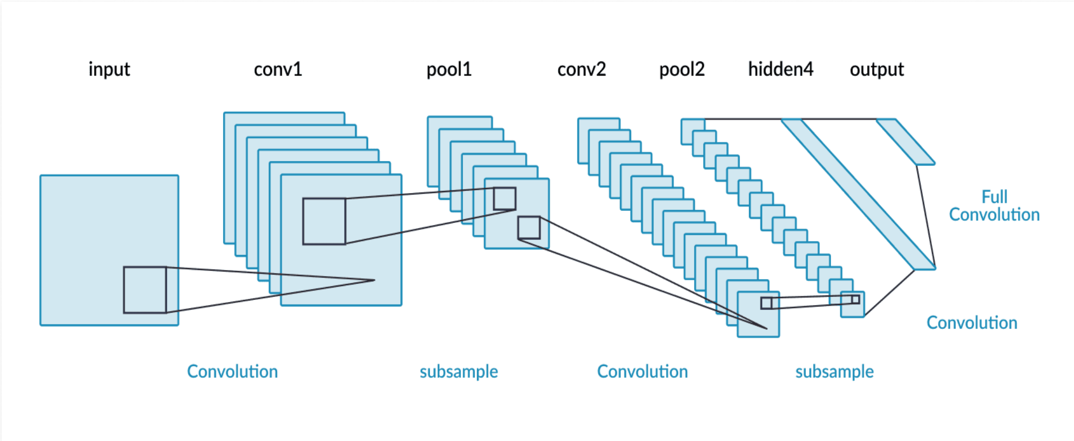


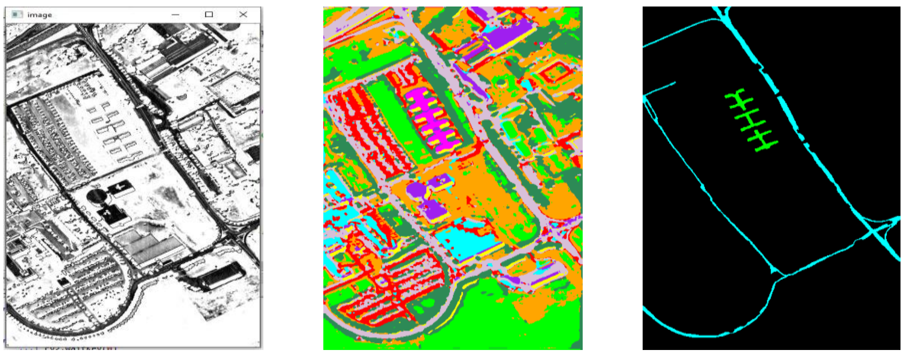
Fig 2: key components of Convolutional Neural Networks (CNN)

Convolutional neural networks are commonly used to solve problems the image classification, as well as fully connected layer is a final layer. In this paper, we investigate the misclassified instances in image recognition in order to achieve a better understanding of deep learning. In generally, we offer an algorithm for the tracking of activated pixels between the final layers of the maps. Then, using the feature tracking algorithm that can visualize the shape features which lead to the misclassification. A comparison of the activated pixels shows which detect and extract the buildings and road. The common pixels activation is important for the classification result.

7. Experimental Dataset

7.1. Pavia University data

The first dataset was created using FCN and SVM methods and images. ROSIS sensor captured during a flight campaign in Pavia from northern Italy. For hyperspectral results, there are 103 bands. There are 610*610 pixels at Pavia University, despite the fact that some of the samples in the image insufficient details and must be removed before use. The spectral resolution range is 1.3 meters. The image ground truth is classified into nine groups. In the statistics, the discarded samples can be interpreted as black stripes abroad. Figure 7 represents a false composite image (R-G-B=band 10-27-46) and the corresponding ground truth reality. Table 2 summarizes the number of samples from training and analysis. In the article, we extracted 103 bands.

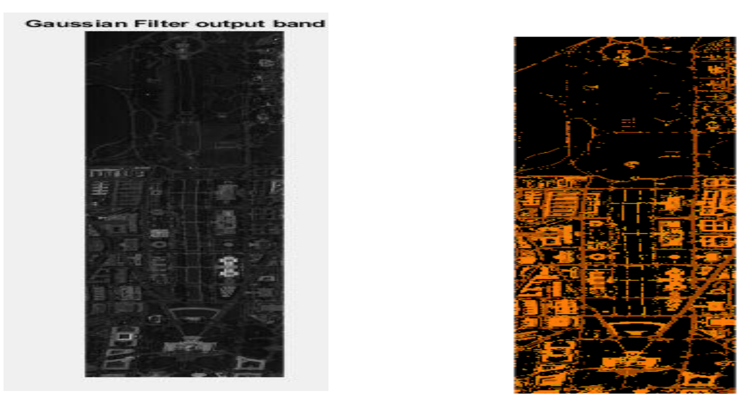


PredictionBan ds results | Classification results | Building & Road prediction

Fig 3:The results of the Pavia datasets of classification

7.2. Washington DC Mall data

In the second dataset hyperspectral images are typically rich in texture. For example, Figure 9(a) shows a simulated color infrared view with hyperspectral data flight line over many details of the airborne “Washington DC Mall” Using FCN and SVM. In this case, the sensor device used measured the pixel response in the 210 bands within the 0.4 to 2.4 µm visible and infrared spectrum region. In the 0.9 and 1.4 µm regions where the atmosphere is invisible, only 191 bands were removed from the dataset. In the case of red, green, and blue colors, the color images are rendered using bands 60, 27, and 17, respectively.

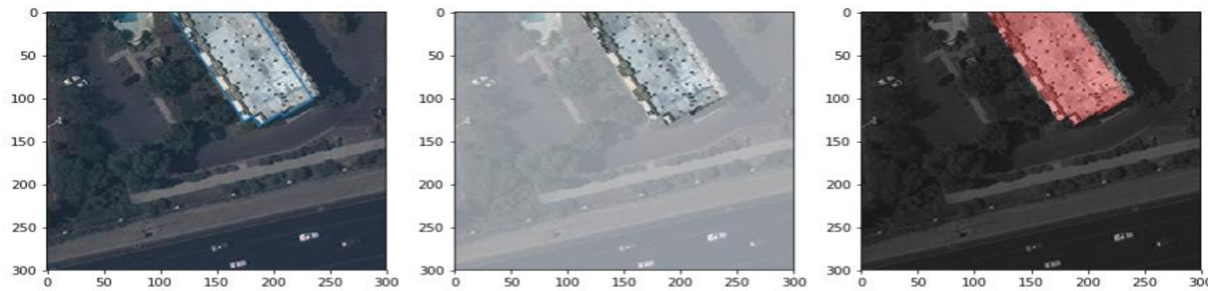


Bands with | Final Results

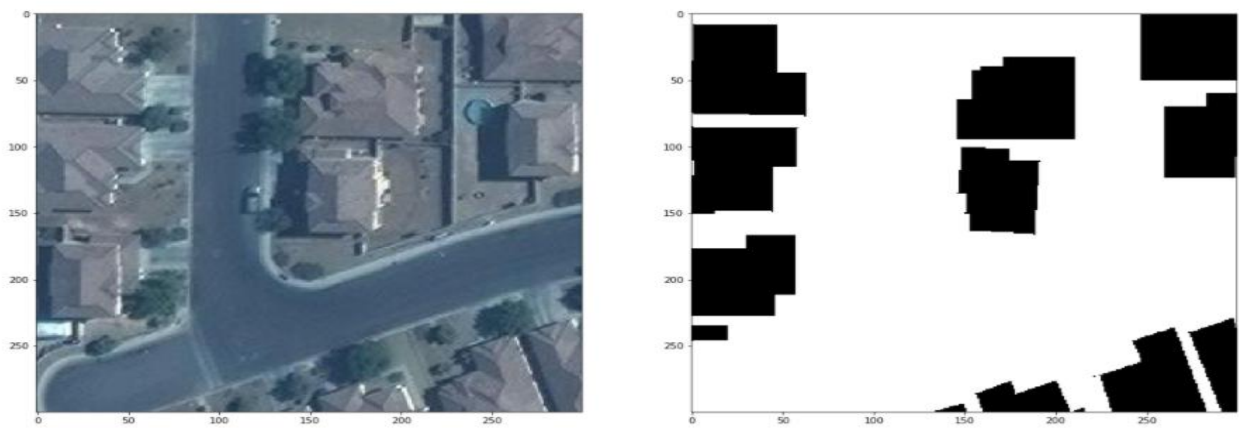
Fig 4:The results of theWashington DC mall datasets of classification

7.3. United States (US) dataset

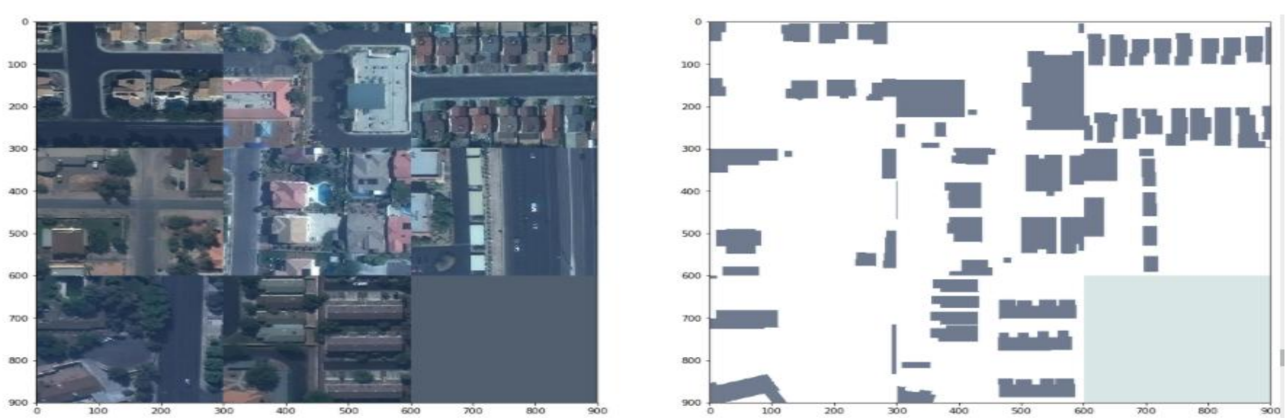
In third hyperspectral images are captured by airborne sensor taken in the United States (US). For hyperspectral training,210 bands of (as 300*300-pixel image) satellite imagery, along with their corresponding annotations in MS-COCO format.Here we took and analyzed 16 bands of the images and extracted building and road features.



Original Image (a) Ground Truth(b) Prediction (c)



Original Image(a) Prediction (b)



Original Image(a) Prediction(b)

Fig 5:The results of theUnited State datasets of classification

8. Result and Discussion

In this paper, we proposed a comparison between three classification methods as FCN, SVM, and CNN. Also, the results of the experiments performed in the study. Using hyperspectral imagery to extract the building footprint and road detection.

Performance of the analysis of the proposed classifier's variations

The objectives of the test which was performed on the differences of the selected classifier are discussed in this sub-section. The system will be correctly designed and trained to achieve high accuracy and extracted road and building values. Executed by considering the images in a representative are with a particular emphasis on the different characteristics of the building and road environment.

S: No	Methods	Road	Building	OA
1	ELM (36)	64.45	90.60	77.52
2	SVM	78.34	91.47	84.90
3	3D-CNN (37)	90.66	56.79	73.72
4	FCNN (36)	93.58	88.55	91.06
5	SS3FCN (37)	93.48	92.72	93.1
6	**FCN**	**92.52**	**90.72**	**91.62**

Table 1: classification performances in (%) of various techniques for the Pavia university data

S: No	Methods	Road	Building	OA
1	PNN (38)	32.71	36.51	34.61
2	3D-CNN (39)	36.48	39.17	37.83
3	PFCN&GDL (40)	38.38	40.27	39.32
4	FCN	42.61	47.50	45.05
5	**SVM**	**56.19**	**52.29**	**54.24**

Table 2: classification performance in (%) of various for the DC Mall data

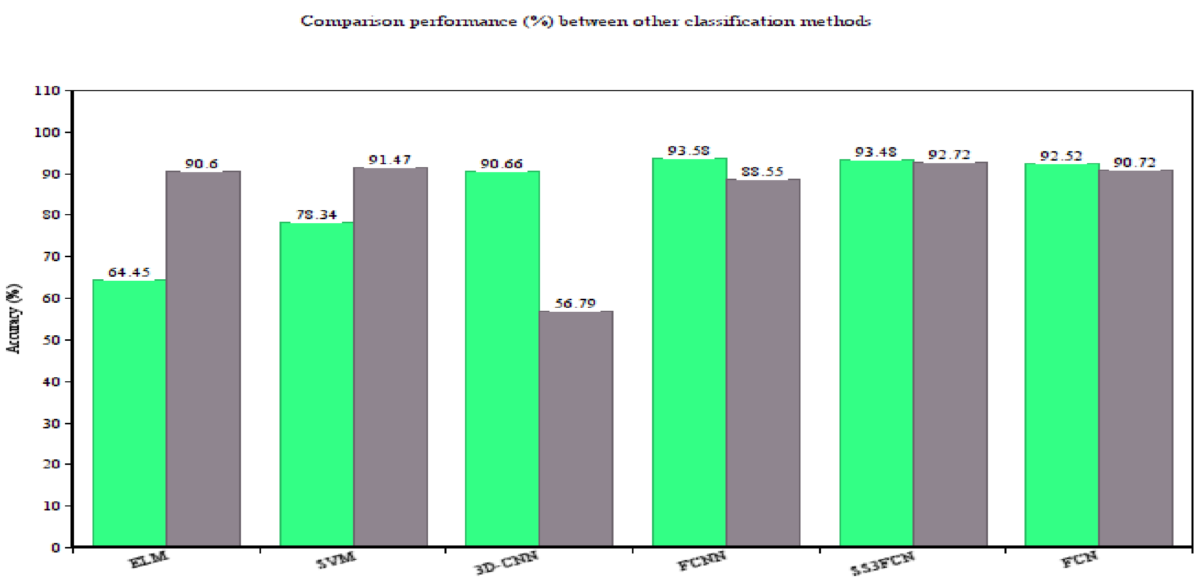
S: No	Datasets	Methods	Classification Accuracy
1	Pavia	FCN	92%
2	Washington DC Mall	SVM	76%
3	United State (US)	CNN	97%

Table 3: Overall classification accuracywith proposed techniques

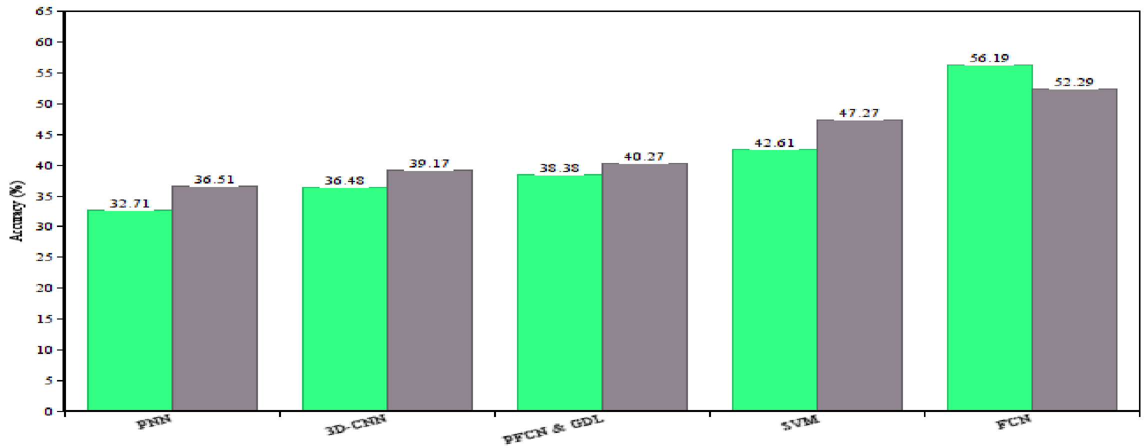
Table 4 describes the computational complexity of the proposed original FCN, SVM, and CNN training and testing procedures. Comparing to the other two techniques, CNN takes much execution time. but accuracy and feature extraction of buildings, road detection is performed very well. It's important to note that the training and testing processes for CNN consume less time than for FCN and SVM. The end result will have far less convolutional and completely linked with layers, which may explain the training techniques. Besides, the input data size of the former (to a network) is far lower than the latter. The computational complexity of the combined classification image pixel model makes CNN a little time-consuming during the research process.

Table 4: Training and testing procedures execution time (h: hours: s: seconds) with three experimental datasets

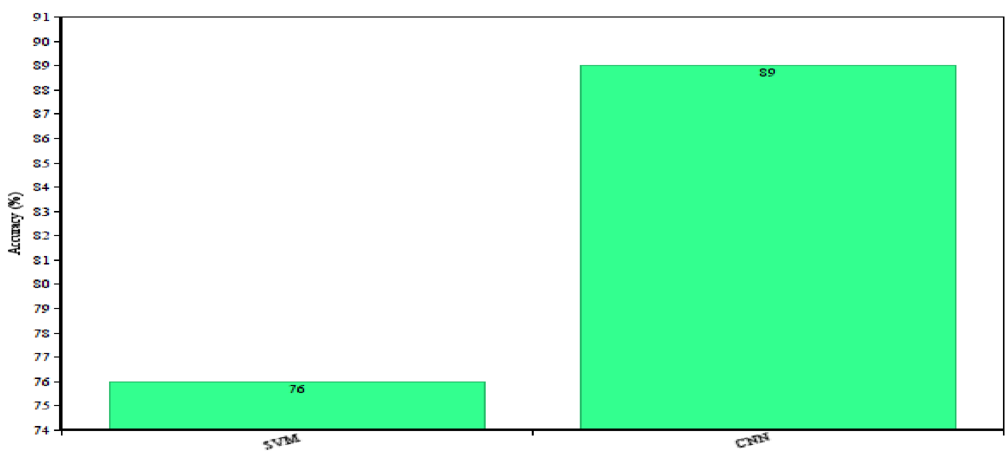
	***h:* hours *s:* seconds**	**University of Pavia**	**Washington DC Mall**	**United State (Washingto**	**Accurac y (%)**
FCN	training *(h)* testing *(s)*	0.8 4.26	-	-	92%
SVM	training *(h)* testing *(s)*	-	0.5 9.79	-	72%
CNN	training *(h)* testing *(s)*	-	-	1.0 20.21	97%
	Size	610*610 103 bands	307*307 210 bands	300*300 100 bands	



Comparison performance (%) between other classification methods



Comparison performance (%) between SVM and CNN



9. Conclusion

The classification of hyperspectral imagery was implemented, evaluated, and compared using three different algorithms based on machine learning and deep learning. This research compares the classification accuracy of Support vector machine, fully convolutional network, and Convolutional neural networks. When compared to SVM and FCN, the CNN has higher overall accuracy. Since satellite imagery is a time-consuming and expensive task for manual road detection and building extraction.Hence automated road detection, and building extraction methods have occurred at a time and its cost-effective solution with limited user participation. To solve this, we proposed and implemented FCN, SVM, and CNN. When we compared FCN, SVM, and CNN classification accuracy for the building footprint extraction and road detection from hyperspectral imagery, the FCN has got overall accuracy of 92%, SVM is 76% and CNN is 97% respectively. The CNN training and testing time area little high compared to the other FCN and SVM but the feature extraction of the building and road detection performance is outstanding. For this future, we plan to apply advanced deep learning techniques to hyperspectral imagery for dimensionality reduction and pre-processing.

References

1. Lange, J., Cavallaro, G., Götz, M., Erlingsson, E., & Riedel, M. (2018, July). The influence of sampling methods on pixel-wise hyperspectral image classification with 3D convolutional neural networks. In *IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium* (pp. 2087-2090). IEEE.

2. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, *25*, 1097-1105.

3. Chen, Y., Jiang, H., Li, C., Jia, X., &Ghamisi, P. (2016). Deep feature extraction and classification of hyperspectral images based on convolutional neural networks. *IEEE Transactions on Geoscience and Remote Sensing*, *54*(10), 6232-6251.

4. Lakshminarayanan, K., Santhana Krishnan, R., Golden Julie, E., Harold Robinson, Y., Kumar, R., Son, L. H.,&Tien Bui, D. (2020). A new integrated approach based on the iterative super-resolution algorithm and expectation-maximization for face hallucination. *Applied Sciences*, *10*(2), 718.

5. Li, Q., Xu, D., He, X., Wang, Y., Chen, Z., Liu, H., ... & Guo, F. (2013). AOTF based molecular hyperspectral imaging system and its applications on nerve morphometry. *Applied Optics*, *52*(17), 3891-3901.

6. Veera Senthil Kumar, G., Leelawathee, SM., Keerthana, V., and Thushitha, S. (2017) A Novel Approach for Band Selection Using Firefly Algorithm in Hyperspectral Images for Classification. International Journal of Engineering Research & Technology (IJERT), 5 (9), 1-4.

7. Xie, F., Li, F., Lei, C., &Ke, L. (2018). Representative band selection for hyperspectral image classification. *ISPRS International Journal of Geo-Information*, *7*(9), 338.

8. Nagasubramanian, K., Jones, S., Sarkar, S., Singh, A. K., Singh, A., &Ganapathysubramanian, B. (2018). Hyperspectral band selection using genetic algorithm and support vector machines for early identification of charcoal rot disease in soybean stems. *Plant Methods*, *14*(1), 1-13.

9. Sawant, S. S., & Manoharan, P. (2020). Unsupervised band selection based on weighted information entropy and 3D discrete cosine transform for hyperspectral image classification. *International Journal of Remote Sensing*, *41*(10), 3948-3969.

10. Zang, Z., & Mo, D. (2012, October). Comparative Study on Dimension Reduction of Hyperspectral Data for Tree Species between ICA Algorithm and PCA Algorithm. In *International Conference on Artificial Intelligence and Computational Intelligence* (pp. 147-154). Springer, Berlin, Heidelberg.

11. Kolluru, P., Pandey, K., &Padalia, H. (2014). A Unified Framework for dimensionality reduction and classification of hyperspectral data. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, *40*(8), 447.

12. Su, J., Yi, D., Liu, C., Guo, L., & Chen, W. H. (2017). Dimension reduction aided hyperspectral image classification with a small-sized training dataset: experimental comparisons. *Sensors*, *17*(12), 2726.

13. Dong, Y., Du, B., Zhang, L., & Zhang, L. (2017). Dimensionality reduction and classification of hyperspectral images using ensemble discriminative local metric learning. *IEEE Transactions on Geoscience and Remote Sensing*, *55*(5), 2509-2524.

14. Haut, J. M., Paoletti, M. E., Plaza, J., & Plaza, A. (2018). Fast dimensionality reduction and classification of hyperspectral images with extreme learning machines. *Journal of Real-Time Image Processing*, *15*(3), 439-462.

15. Zhong, Y., Zhang, L., Huang, B., & Li, P. (2006). An unsupervised artificial immune classifier for multi/hyperspectral remote sensing imagery. *IEEE Transactions on Geoscience and Remote Sensing*, *44*(2), 420-431.

16. Wang, C., Guo, Z., Wang, S., Wang, L., & Ma, C. (2015). Improving hyperspectral image classification method for fine land use assessment application using semisupervised machine learning. *Journal of Spectroscopy*, *2015*.

17. Makantasis, K., Karantzalos, K., Doulamis, A., &Loupos, K. (2015, December). Deep learning-based man-made object detection from hyperspectral data. In *International Symposium on Visual Computing* (pp. 717-727). Springer, Cham.

18. Guo, Z., Shao, X., Xu, Y., Miyazaki, H., Ohira, W., &Shibasaki, R. (2016). Identification of village buildings via Google Earth images and supervised machine learning methods. *Remote Sensing*, *8*(4), 271.

19. Mou, L., Ghamisi, P., & Zhu, X. X. (2017). Deep recurrent neural networks for hyperspectral image classification. *IEEE Transactions on Geoscience and Remote Sensing*, *55*(7), 3639-3655.

20. Thanh Noi, P., &Kappas, M. (2018). Comparison of random forest, k-nearest neighbor, and support vector machine classifiers for land cover classification using Sentinel-2 imagery. *Sensors*, *18*(1), 18.

21. Nahhas, F. H., Shafri, H. Z., Sameen, M. I., Pradhan, B., &Mansor, S. (2018). Deep learning approach for building detection using lidar–orthophoto fusion. *Journal of Sensors*, *2018*.

22. Shrestha, S., &Vanneschi, L. (2018). Improved fully convolutional network with conditional random fields for building extraction. *Remote Sensing*, *10*(7), 1135.

23. Li, X., Zhang, L., & You, J. (2018). Hyperspectral image classification based on two-stage subspace projection. *Remote Sensing*, *10*(10), 1565.

24. Hasan, M., Ullah, S., Khan, M. J., & Khurshid, K. (2019). Comparative Analysis of SVM ANN And CNN For Classifying Vegetation Species Using Hyperspectral Thermal Infrared Data. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*.

25. Guo, Y., Yin, X., Zhao, X., Yang, D., & Bai, Y. (2019). Hyperspectral image classification with SVM and guided filter. *EURASIP Journal on Wireless Communications and Networking*, *2019*(1), 1-9.

26. Zhang, Y., Jiang, X., Wang, X., & Cai, Z. (2019). Spectral-spatial hyperspectral image classification with superpixel pattern and extreme learning machine. *Remote Sensing*, *11*(17), 1983.

27. Zhang, C., Yue, J., & Qin, Q. (2020). Deep quadruplet network for hyperspectral image classification with a small number of samples. *Remote Sensing*, *12*(4), 647.

28. Road Accidents in India (2018) Government of India Ministry of Road Transport Wing.

29. Road Accident Analysis in Tamil Nadu (2019). Government of Tamil Nadu home (Transport) Department.
30. World Health Organization WHO Regional Websites (2020).

31. Petropoulos, G. P., Arvanitis, K., Sigrimis, N., Piromalis, D. D., &Boglou, A. K. (2012, November). Land use cartography from Hyperion hyperspectral imagery analysis: Results from a Mediterranean site. In *2012 IEEE 24th International Conference on Tools with Artificial Intelligence* (Vol. 2, pp. 26-31). IEEE.

32. Praharaj, S., Han, J. H., & Hawken, S. (2018). Towards the right model of smart city governance in India. *Sustainable Development Studies*, 13, 171–186.

33. Gavankar, N. L., & Ghosh, S. K. (2018). Automatic building footprint extraction from high-resolution satellite image using mathematical morphology. *European Journal of Remote Sensing*, *51*(1), 182-193.

34. Chawda, C., Aghav, J., &Udar, S. (2018, September). Extracting Building Footprints from Satellite Images using Convolutional Neural Networks. In *2018 International Conference on Advances in Computing, Communications, and Informatics (ICACCI)* (pp. 572-577). IEEE.

35. Vapnik, V.N., Vapnik, V., 1998. Statistical learning theory. Wiley New York.

36. Li, J., Zhao, X., Li, Y., Du, Q., Xi, B., & Hu, J. (2018). Classification of hyperspectral imagery using a new fully convolutional neural network. *IEEE Geoscience and Remote Sensing Letters*, *15*(2), 292-296.

37. Zou, L., Zhu, X., Wu, C., Liu, Y., & Qu, L. (2020). Spectral–Spatial Exploration for Hyperspectral Image Classification via the Fusion of Fully Convolutional Networks. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 659-674.

38. Masi, G., Cozzolino, D., Verdoliva, L., & Scarpa, G. (2016). Pansharpening by convolutional neural networks. *Remote Sensing*, *8*(7), 594.

39. Palsson, F., Sveinsson, J. R., &Ulfarsson, M. O. (2017). Multispectral and hyperspectral image fusion using a 3-D-convolutional neural network. *IEEE Geoscience and Remote Sensing Letters*, *14*(5), 639-643.

40. Zhou, F., Hang, R., Liu, Q., & Yuan, X. (2019). Pyramid fully convolutional network for hyperspectral and multispectral image fusion. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *12*(5), 1549-1558.