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Landsat-8 Image Classification using Support Vector Machine Classifier

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ABSTRACT

The extent of Built-up Area (BUA) is continuously increasing with rapid globalization. Identification of BUA provides vital information required for territorial planning as well as the impact of land cover changes on the environment. Therefore, detection of changes in land cover should be carried out periodically. However, it is difficult to extract built-up areas using satellite images because of the confusion between spectral values with other land cover types. Presently, satellite sensors provide continuous data in multiple spectral channels, which are becoming very useful for monitoring earth surface over large areas. The primary challenge is to accurately retrieve class information from the enormous set of data.

The selected study area comprises of a scene taken from Haridwar District, India. The bounding coordinates of the chosen area are, long. 77 48’ 32.4’’ E and Lat. 29 54’ 50.4’’ N at upper left and long. 77 57’ 28.8’’ E and Lat. 29 45’ 46.8’’ N at lower right. In the last few decades, rapid urbanization has been taken place in this area, which results in increased infrastructural growth and urban expansion. The area mainly consists of land cover types such as built-up regions, agricultural land, water bodies, river sand and fallow land.

The satellite data used in this study consists of multispectral bands acquired by Landsat-8 Operation Land Imager (OLI) sensor on 10 December 2014 with path- row number 146-39. The image represents a diverse land class scenario with 572 463 pixels in seven bands ranging from the wavelength of 0.43–2.29lm in the spectrum and having a spatial resolution of 30 m. In this study, medium resolution Landsat-8 data is used because it is suitable for mapping of land cover classes such as built-up area.

However, the conventional methods are failed to provide the accurate classification performance. So, this work considered the machine learning based Support Vector Machine (SVM) classifier for obtaining the labelled samples from Landsat-8 Image.

Keywords: Landsat 8 image, Support vector machine, Built-up area.

1. INTRODUCTION

Land use/land cover classification at the global scale is one of the challenges of geospatial analysis. Providing a unified categorization of types of human habitats, as well as of land cover in rural areas, faces great challenges, since the structures of cities vary greatly depending on architectural, cultural, and environmental local conditions. Nonetheless, the payback for a successful characterization would be enormous, since this would allow a better calibration of climatic models [1], successful intercities comparisons [2] and, in general, an objective way of describing cities and their impacts on the environment.

Despite the existence of global built-up layers, such as the Global Urban Footprint [3] and the Global Built-up Density of the ESA Urban Thematic Exploitation Platform [4] and the Global Urban Human Settlements Layer of the Joint Research Center of the European Commission [5], or of regional/continental initiatives such as the Copernicus Urban Atlas in the European Union [6], we are still lacking a unified view of land use in multiple categories describing how the urban space is structured. When considering land use, it becomes important to consider densities, layouts, and volumes, since most categories will be characterized by buildings and trees, and what will differentiate them is how they are organized.

2. LITERATURE SURVEY

Yokoya et. al [1] presented the scientific outcomes of the 2017 Data Fusion Contest organized by the Image Analysis and Data Fusion Technical Committee of the IEEE Geoscience and Remote Sensing Society. The 2017 Contest was aimed at addressing the problem of local climate zones classification based on a multitemporal and multimodal dataset, including image (Landsat 8 and Sentinel-2) and vector data (from OpenStreetMap). The competition, based on separate geographical locations for the training and testing of the proposed solution, aimed at models that were accurate (assessed by accuracy metrics on an undisclosed reference for the test cities), general (assessed by spreading the test cities across the globe), and computationally feasible (assessed by having a test phase of limited time). The techniques proposed by the participants to the Contest spanned across a rather broad range of topics, and of mixed ideas and methodologies deriving from computer vision and machine learning but also deeply rooted in the specificities of remote sensing. In particular, rigorous atmospheric correction, the use of multidate images, and the use of ensemble methods fusing results obtained from different data sources/time instants made the difference.

Liu et. al [2] proposes a multitask deep learning method that simultaneously conducts classification and reconstruction in the open world (named MDL4OW) where unknown classes may exist. The reconstructed data are compared with the original data; those failing to be reconstructed are considered unknown based on the assumption that they are not well represented in the latent features due to the lack of labels. A threshold needs to be defined to separate the unknown and known classes; we propose two strategies based on the extreme value theory for few- and many-shot scenarios. The proposed method was tested on real-world hyperspectral images; state-of-the-art results were achieved, e.g., improving the overall accuracy by 4.94% for the Salinas data. By considering the existence of unknown classes in the open world, our method achieved more accurate hyperspectral image classification, especially under the few-shot context.

Xu et. al [3] presents the scientific outcomes of the 2018 Data Fusion Contest organized by the Image Analysis and Data Fusion Technical Committee of the IEEE Geoscience and Remote Sensing Society. The 2018 Contest addressed the problem of urban observation and monitoring with advanced multi-source optical remote sensing (multispectral LiDAR, hyperspectral imaging, and very high-resolution imagery). The competition was based on urban land use and land cover classification, aiming to distinguish between very diverse and detailed classes of urban objects, materials, and vegetation. Besides data fusion, it also quantified the respective assets of the novel sensors used to collect the data. Participants proposed elaborate approaches rooted in remote-sensing, and also in machine learning and computer vision, to make the most of the available data. Winning approaches combine convolutional neural networks with subtle earth-observation data scientist expertise.

Sun et. al [4] proposed a spectral-spatial attention network (SSAN) to capture discriminative spectral-spatial features from attention areas of HSI cubes. First, a simple spectral-spatial network (SSN) is built to extract spectral-spatial features from HSI cubes. The SSN is composed of a spectral module and a spatial module. Each module consists of only a few 3-D convolution and activation operations, which make the proposed method easy to converge with a small number of training samples. Second, an attention module is introduced to suppress the effects of interfering pixels. The attention module is embedded into the SSN to obtain the SSAN. The experiments on several public HSI databases demonstrate that the proposed SSAN outperforms several state-of-the-art methods.

Luo et. al [5] propose a hybrid-graph learning method to reveal the complex high-order relationships of the HSI, termed enhanced hybrid-graph discriminant learning (EHGDL). In EHGDL, an intraclass hypergraph and an interclass hypergraph are constructed to analyze the complex multiple relationships of an HSI. Then, a supervised locality graph is applied to reveal the binary relationships of a HSI which can form the complementarity of a hypergraph. Simultaneously, we also construct a weighted neighborhood margin model to boost the difference of samples from different classes. Finally, we design a DR model based on the intraclass hypergraph, the interclass hypergraph, the supervised locality graph, and the weighted neighborhood margin to improve the compactness of the intraclass samples and the separability of the interclass samples, and an optimal projection matrix can be achieved to extract the low-dimensional embedding features of the HSI. To demonstrate the effectiveness of the proposed method, experiments have been conducted on the Indian Pines, PaviaU, and HoustonU data sets. The experimental results show that EHGDL can generate better classification performance compared with some related DR methods. As a result, EHGDL can better reveal the complex intrinsic relationships of a HSI by the complementarity of different characteristics and enhance the discriminant performance of land-cover types.

Zhu et. al [6] proposed an end-to-end residual spectral-spatial attention network (RSSAN) for HSI classification. The RSSAN takes raw 3-D cubes as input data without additional feature engineering. First, a spectral attention module is designed for spectral band selection from raw input data by emphasizing useful bands for classification and suppressing useless bands. Then, a spatial attention module is designed for the adaptive selection of spatial information by emphasizing pixels from the same class as the center pixel or those are useful for classification in the pixel-centered neighborhood and suppressing those from a different class or useless. Second, two attention modules are also used in the following CNN for adaptive feature refinement in spectral-spatial feature learning. Third, a sequential spectral-spatial attention module is embedded into a residual block to avoid overfitting and accelerate the training of the proposed model. Experimental studies demonstrate that the RSSAN achieved superior classification accuracy compared with the state of the art on three HSI data sets: Indian Pines (IN), University of Pavia (UP), and Kennedy Space Center (KSC).

Hang et. al [7] proposed a cascaded RNN model using gated recurrent units to explore the redundant and complementary information of HSIs. It mainly consists of two RNN layers. The first RNN layer is used to eliminate redundant information between adjacent spectral bands, while the second RNN layer aims to learn the complementary information from nonadjacent spectral bands. To improve the discriminative ability of the learned features, we design two strategies for the proposed model. Besides, considering the rich spatial information contained in HSIs, we further extend the proposed model to its spectral-spatial counterpart by incorporating some convolutional layers. To test the effectiveness of our proposed models, we conduct experiments on two widely used HSIs. The experimental results show that our proposed models can achieve better results than the compared models.

Chen et. al [8] proposed the idea of automatic CNN for the HSI classification for the first time. First, a number of operations, including convolution, pooling, identity, and batch normalization, are selected. Then, a gradient descent-based search algorithm is used to effectively find the optimal deep architecture that is evaluated on the validation data set. After that, the best CNN architecture is selected as the model for the HSI classification. Specifically, the automatic 1-D Auto-CNN and 3-D Auto-CNN are used as spectral and spectral-spatial HSI classifiers, respectively. Furthermore, the cutout is introduced as a regularization technique for the HSI spectral-spatial classification to further improve the classification accuracy. The experiments on four widely used hyperspectral data sets (i.e., Salinas, Pavia University, Kennedy Space Center, and Indiana Pines) show that the automatically designed data-dependent CNNs obtain competitive classification accuracy compared with the state-of-the-art methods. In addition, the automatic design of the deep learning architecture opens a new window for future research, showing the huge potential of using neural architectures' optimization capabilities for the accurate HSI classification.

Hang et. al [9] proposed an attention-aided CNN model for spectral-spatial classification of hyperspectral images. Specifically, a spectral attention subnetwork and a spatial attention subnetwork are proposed for spectral and spatial classifications, respectively. Both of them are based on the traditional CNN model and incorporate attention modules to aid networks that focus on more discriminative channels or positions. In the final classification phase, the spectral classification result and the spatial classification result are combined together via an adaptively weighted summation method. To evaluate the effectiveness of the proposed model, we conduct experiments on three standard hyperspectral data sets. The experimental results show that the proposed model can achieve superior performance compared with several state-of-the-art CNN-related models.

Capolupo et. al [10] proposed a new Landsat Images Classification Algorithm (LICA) to automatically detect land cover (LC) information using satellite open data provided by different Landsat missions in order to perform a multitemporal and multisensors analysis. All the steps of the proposed method were implemented within Google Earth Engine (GEE) to automatize the procedure, manage geospatial big data, and quickly extract land cover information. The algorithm was tested on the experimental site of Siponto, a historic municipality located in Apulia Region (Southern Italy) using 12 radiometrically and atmospherically corrected satellite images collected from Landsat archive (four images, one for each season, were selected from Landsat 5, 7, and 8, respectively). Those images were initially used to assess the performance of 82 traditional spectral indices. Since their classification accuracy and the number of identified LC categories were not satisfying, an analysis of the different spectral signatures existing in the study area was also performed, generating a new algorithm based on the sequential application of two new indices (SwirTirRed (STRed) index and SwiRed index). The former was based on the integration of shortwave infrared (SWIR), thermal infrared (TIR), and red bands, whereas the latter featured a combination of SWIR and red bands. The performance of LICA was preferable to those of conventional indices both in terms of accuracy and extracted classes number (water, dense and sparse vegetation, mining areas, built-up areas versus water, and dense and sparse vegetation). GEE platform allowed us to go beyond desktop system limitations, reducing acquisition and processing times for geospatial big data.

Zhang et. al [11] proposed a novel multi-scale deep learning model, namely ASPP-Unet and ResASPP-Unet for urban land cover classification based on very high resolution (VHR) satellite imagery. The proposed ASPP-Unet model consists of a contracting path which extracts the high-level features, and an expansive path, which up-samples the features to create a high-resolution output. The atrous spatial pyramid pooling (ASPP) technique is utilized in the bottom layer in order to incorporate multi-scale deep features into a discriminative feature. The ResASPP-Unet model further improves the architecture by replacing each layer with residual unit. The models were trained and tested based on WorldView-2 (WV2) and WorldView-3 (WV3) imageries over the city of Beijing. Model parameters including layer depth and the number of initial feature maps (IFMs) as well as the input image bands were evaluated in terms of their impact on the model performances. It is shown that the ResASPP-Unet model with 11 layers and 64 IFMs based on 8-band WV2 imagery produced the highest classification accuracy (87.1% for WV2 imagery and 84.0% for WV3 imagery). The ASPP-Unet model with the same parameter setting produced slightly lower accuracy, with overall accuracy of 85.2% for WV2 imagery and 83.2% for WV3 imagery. Overall, the proposed models outperformed the state-of-the-art models, e.g., U-Net, convolutional neural network (CNN) and Support Vector

Machine (SVM) model over both WV2 and WV3 images, and yielded robust and efficient urban land cover classification results.

Phan et. al [12] analyzed the effect of different composition methods, as well as different input images, on the classification results. We use Landsat 8 surface reflectance (L8sr) data with eight different combination strategies to produce and evaluate land cover maps for a study area in Mongolia. We implemented the experiment on the GEE platform with a widely applied algorithm, the Random Forest (RF) classifier. Our results show that all the eight datasets produced moderately to highly accurate land cover maps, with overall accuracy over 84.31%. Among the eight datasets, two time series datasets of summer scenes (images from 1 June to 30 September) produced the highest accuracy (89.80% and 89.70%), followed by the median composite of the same input images (88.74%). The difference between these three classifications was not significant based on the McNemar test ($p > 0.05$). However, significant difference ($p < 0.05$) was observed for all other pairs involving one of these three datasets. The results indicate that temporal aggregation (e.g., median) is a promising method, which not only significantly reduces data volume (resulting in an easier and faster analysis) but also produces an equally high accuracy as time series data. The spatial consistency among the classification results was relatively low compared to the general high accuracy, showing that the selection of the dataset used in any classification on GEE is an important and crucial step, because the input images for the composition play an essential role in land cover classification, particularly with snowy, cloudy and expansive areas like Mongolia.

3. PROPOSED SYSTEM

Support Vector Machine Algorithm (SVM)

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

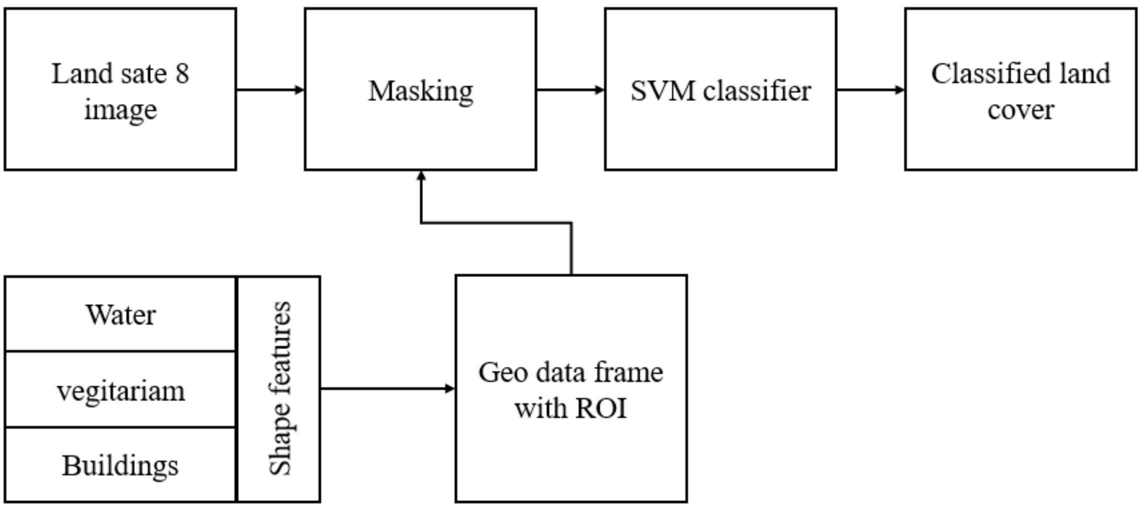
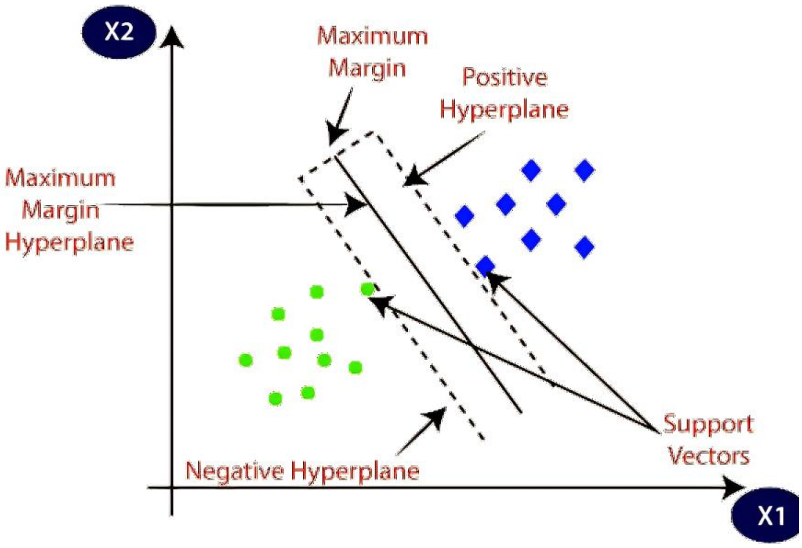


Fig. 1: Block diagram of proposed system.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:



What is text classification in SVM?

Text Classification is the process of labeling or organizing text data into groups – it forms a fundamental part of Natural Language Processing. In the digital age that we live in, we are surrounded by text on our social media accounts, commercials, websites, Ebooks, etc. The majority of this text data is unstructured, so classifying this data can be extremely useful.

Columns

- UserName
- ScreenName
- Location
- TweetAt
- OriginalTweet
- Sentiment

Applications

- Face recognition
- Weather prediction
- Medical diagnosis
- Spam detection
- Age/gender identification
- Language identification
- Sentimental analysis
- Authorship identification
- News classification

Advantages of proposed system

- SVM works relatively well when there is a clear margin of separation between classes.
- SVM is more effective in high dimensional spaces.

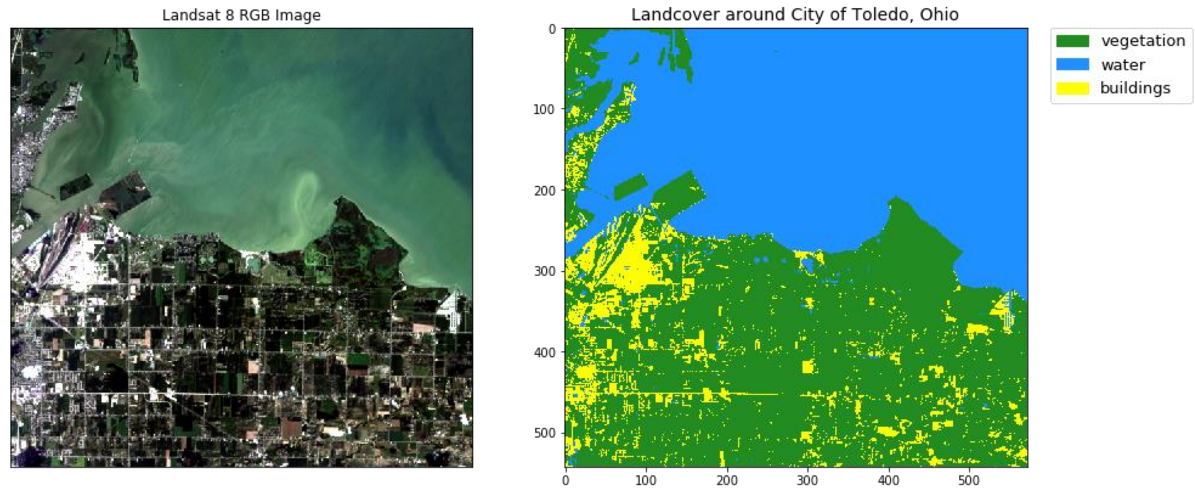
- SVM is effective in cases where the number of dimensions is greater than the number of samples.
- SVM is relatively memory efficient.

4. RESULTS AND DISCUSSION

	CLASS_NAME	CLASS_ID	CLASS_CLRS	geometry
0	vegetation	1	0,128,0	POLYGON ((297795 4624995, 297795 4624965, 2977...
1	vegetation	1	0,128,0	POLYGON ((294375 4624515, 294375 4624485, 2943...
2	vegetation	1	0,128,0	POLYGON ((294645 4623435, 294645 4623405, 2946...
3	vegetation	1	0,128,0	POLYGON ((306285 4618545, 306285 4618515, 3062...
4	vegetation	1	0,128,0	POLYGON ((306975 4617405, 306975 4617375, 3069...
...	...	...	...	...
25	buildings	3	255,0,0	POLYGON ((299265 4612305, 299265 4612275, 2992...
26	buildings	3	255,0,0	POLYGON ((298785 4612275, 298785 4612245, 2987...
27	buildings	3	255,0,0	POLYGON ((293775 4612215, 293775 4612185, 2937...
28	buildings	3	255,0,0	POLYGON ((296835 4612185, 296835 4612155, 2968...
29	buildings	3	255,0,0	POLYGON ((305475 4610955, 305475 4610925, 3054...

90 rows × 4 columns

The index column of 'joinframe' consists of three sets of 0 to 29 values. Replaced the index column with numbers from 0 to 89.



5. CONCLUSION

This work presented SVM algorithm created for calculating the LST from LANDSAT 8 TIRS. The algorithm was derived using the observed thermal radiance of the TIRS Band 10 of LANDSAT 8. To verify the final retrieved LST results, the near-surface air temperature method was used. The selected study area comprises of a scene taken from Haridwar District, India. The bounding coordinates of the chosen area are, long. 77 48’ 32.4’’ E and Lat. 29 54’ 50.4’’ N at upper left and long. 77 57’ 28.8’’ E and Lat. 29 45’ 46.8’’ N at lower right. In the last few decades, rapid urbanization has been taken place in this area, which results in increased infrastructural growth and urban expansion.

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