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# An Analysis on Intelligent Systems for Remote Sensing Satellite Image Processing and Classification

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***Abstract:** The integration of intelligent systems to the remote sensing satellite image processing and classification has greatly changed. This paper offers a synthesis of the subject, with respect to intelligent systems' contribution to the improvement of these processes' accuracy and speed. Accuracy of different methods such as machine learning algorithms, artificial neural networks, and deep learning techniques in the extraction of information from satellite image comprehension is considered a research interest. The presented problems and open issues are data complexity, feature extraction, and classification accuracy over the data, along with new methods in enhancing the intelligent systems to minimize those problems. It expands knowledge of intelligent systems' contribution to remote sensing applications by outlining how these advancements have influenced the progression of image analysis for the given research goals. This research work gives the summary of our research by outlining the techniques used in the study, the problems solved, and the general outcomes of incorporating intelligent systems in the area of remote sensing and satellite image analysis. Accuracy analysis results for the SVM based methodology with spatial-spectral features include 90% of accuracy, 88% of the precision, and 90% of the F1-score, which in turn makes it easy to make sound decisions when using satellite imagery in different fields like agriculture, urban development, and environment.***

***Keywords:** Intelligent Systems, Remote Sensing, Image Processing, Satellite Images and Artificial Intelligence, And Classification.***

## 1. INTRODUCTION

The field of remote sensing [1] indeed has opened up tremendous prospects for not only monitoring of the environment and utilization of resources but also in the management and mitigation of natural disasters through enhancements in satellite remote sensing technology. Paradoxically, the more satellite imagery data is accumulated, the greater a demand appears

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for the improving intelligent systems that can work on these huge datasets. More specifically, the objectives of this research are as follows:
This research seeks to reveal an understanding of intelligent systems that focus on the analysis of RS satellite images and classification with an emphasis on comprehensive research on intelligent satellite image processing and segmentation [2]. These systems utilize advanced methods of AI, ML, and Computer Vision which help in making the extraction of useful data from satellite images more efficient. Through the combination of these technologies, it is identified that researchers can improve the effectiveness, efficiency and further expand the image analysis application in various fields.

This paper's primary concern is to identify the techniques and approaches used by intelligent systems in the areas of satellite image analysis and categorization [3]. This involves the adoption of deep learning techniques including CNN for feature extraction and classification tasks besides feature ensemble with the view of enhancing classification accuracy. Furthermore, the research will also consider the fusion of multi-spectral and multi-spatial information which involves both the spectral data set and spatial data set of satellite imagery to improve the distinctiveness of classification outcomes. Being aware of those approaches is essential for further development of this field and dealing with the issues like heterogeneity of data, cloud presence, and scale differences in relation to satellite images.

Moreover, this research will also assess the current performance indicators in judging the competence of intelligent systems in satellite image analysis and categorization. Performance indicators including; general accuracy, precision, recall, and the F1 score will be computed to help explain how effective these systems are in different locations, and under different environmental conditions. Further, the research will explore the methods of handling problems including, insufficient data, noisy labels, and domain shift problems that are often encountered in the context of satellite imagery data sets. With respect to these issues, the researchers can improve the stability and credibility of the intelligent systems in real life applications.

Thus the finding and contribution of this research transcend academic pursuit of knowledge to inform policy-makers, scientists, and other stakeholders in the satellite monitoring and decision-making programs [4]. In the case where organizations invest in intelligent systems, business processes can be automated which will mean that human input is minimal, and therefore timely information about changing environments can be obtained. Furthermore, further development of this sphere will enable local people and governing bodies to analyze satellite information, apply it to the usage of territories that has affected by human activity, design infrastructures based on this critical data, and assess the consequences of emergencies.
Intelligent systems for remote sensing satellite image preprocessing and classification forms one of the core research areas that have massive impacts on environmental stewardship and the quality of life. Through the implementation of AI and machine learning [5]-[7], new opportunities for studying the processes happening on our planet at the global level are possible. To this end, this research endeavour aims at enhancing the establishment of new and improved RS technology to advance knowledge and utilisation in a range of domains comprehensively.

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Raise in the applications of AI and machine learning [8]-[10] has had a significant impact on the remote sensing satellite image processing and classification by providing rich and well-developed algorithms to process and interpret large amounts of satellite data. These techniques include a number of methods and algorithms that are specifically designed for satellite imagery analysis, the major issues of which are the high dimensionality of data, spatial characteristics and variability of the environment.

## 2. LITERATURE REVIEW

The remote sensing program commenced with the help of NASA [11] in the year 1972 with the application of Landsat-1: thus, the usage of remote sensing happened from the day Landsat-1 was launched, making it a pump in the background of remote sensing. Developing the possibility to capture the multispectral imagery of the earth's surface, it contributed to the further developments in satellite image processing and classification. For many years, Landsat satellites have been useful in recording changes in land cover; physical features including urban expansion and environmental trends. The consistent data accumulation in the procedure has benefited numerous researches and applications, thereby affirming its centrality in the evolvement of remote sensing technology (NASA, 2023).
Jensen [12] written a textbook entitled 'Introduction to Remote Sensing' in which the author incorporated a spatial approach in explaining the principles of remote sensing and their uses. Elements like sensor technology, image interpretation, and proper methods of digital image processing that help in the understanding of what remote sensing is as well as how the data generated by it is collected, analyzed and applied are discussed in the book. It becomes informative for the students, researchers and the scholars who wants to make a career in this field to understand those historical and evolutionary aspect along with the current state of art of Remote Sensing (Jensen, 2005).

Deep learning approaches recommended and introduced by Ma et al. [13] seem to present a fairly exhaustive look into the use of deep learning in remote sensing, and this is about the efficacy of various deep learning technologies in image analysis. In the analysis the author surveys the applications of deep learning and convolutional neural networks in particular for the land cover classification, object detection, and change detection in the satellite imagery. The deep learning models extract superior hierarchical features from raw data, and hence, provide higher accuracy and robustness compared to conventional methodologies; such models are anticipated in different fields including precision agriculture, disaster recovery, and environment control (Ma et al., 2019).
Liakos et al. [14] offer a research on the applications of machine learning in agriculture with focus on advancement in the use of remote sensing technology. The review on the application of satellite imagery also describes the use of machine learning algorithms in supervised and unsupervised learning to monitor crops, predict yields, and manage resources. As such, the above approaches combine satellite data with ground data to produce advanced method practices of agriculture with efficiency, production, and environmental effects. The study also points out at how machine learning enables the farm sector by the provision of data-driven

understandings of the farming responsibilities coupled with efficient operational solutions (Liakos et al., 2018).

He et al. [15] describe deep residual learning as a major advancement in image recognition and this has also been applied in remote sensing. The common problem with training extremely deep networks is solved by using the residual neural network architecture and adding residual connections to allow gradient flow through the network. In remote sensing application, these networks have been extended for applications such as classification of land cover and feature extraction from multispectral & Hyperspectral image. Based on the considerations presented in the study, the analysis of residual networks helps to ensure improved accuracy and robustness for further analysis of spatial and spectral patterns in the satellite images of Earth's surface (He et al., 2016).

Castelluccio et al. [16] continue their research focusing on the use of convolutional neural networks (CNNs) in land cover classification for satellite images. It evolves from the previous approaches of requiring one to design and extract the features required to solve a particular problem from the multispectral data through the utilization of CNNs which automatically learn spatial features from the inputted data. As the facts presented above show, through modification of the hierarchical representation capabilities of CNNs, the method enables to solve land cover mapping and change detection tasks at the level of the state of the art. The study also shows how the deep learning methods can be used for fast and efficient data analysis on large scale satellites imagery incorporating they can be applied for actual environmental assessment and urban planning (Castelluccio et al., 2015).

Reviewing the recent over referenced works, Chen et al. [17] elaborate on the use of deep learning techniques for hyperspectral data classification in remote sensing. The work is devoted to the key ways of modulating the convolutional and recurrent neural networks to benefit from the spectral diversity of hyperspectral images. Spectral signatures are characteristically captured at high resolutions that help RL improve the differentiation of land cover classes hence better mapping of the environment. The work reviews the progress related to the feature learning and the data fusion methods which build upon the ability of deep learning for dealing the high and complex data, the state of the art in the hyperspectral image analysis is improved (Chen et al. , 2017).

In the work by Ghamisi et al., [18] researchers discuss enhanced spectral-spatial classification methods based on deep learning for HSIs. The paper focuses on the fusion of spectral and spatial information under the framework of deep neural networks with the aim of improving the ability of hyperspectral images to distinguish minor spectral changes and spatial features. Convolutional and recurrent structures of the proposed solution allow for high classification performance and environmental stability. The research is beneficial to advance solutions for large scale and accurate LC mapping, minerals exploration, and EnM applications (Ghamisi et al., 2018).
The work of Wang et al. [19] include a detailed review of different approaches to semantic segmentation using deep learning for RS. This paper reviews different deep learning structures

 

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and approaches used in the accurate identification and categorization of different objects and land cover types in satellite imagery. The fully convolutional networks and U-Net have been explained in relation to the level of detail and accuracy in terms of spatial information of multispectral and high-resolution imagery. Thus, the review emphasizes how semantic segmentation advances and develops with the recent progress on different problems and directions for its application to various fields such as urban planning, disaster management, and environmental conservation (Wang et al., 2020).
Muller et al. [20] look into issues and possibilities of XAI in EO / RS. Transparency and interpretability of the AI models to analyze the satellites imagery and the environmental data is also explained in the study. It looks into different methods of XAI which helps the end-users to comprehend the actions made by the AI, to gain their trust and to aid sound decision making in areas like land use planning, biodiverse conservation, and disasters risk reduction. The study highlights the paradigm shift in XAI for RS and calls for more concern on the ethical issue and possible collaboration with other fields to optimize the technology (Muller et al., 2021).
Lu et al. [21] discuss the recent progress on the use of LiDAR data and its analysis and includes in remote sensing. The important subjects to be addressed in the study include data collection and acquisition, processing point cloud data, feature extraction, and 3D modeling in line with LiDAR technology. LiDAR data enhance satellite imagery by providing specific topographical data in terms of elevation and terrain surface which is useful in terrain modeling, mapping of cities and analysis of forest structure. The review also focuses on the current advances in LiDAR data fusion methods with multispectral and hyperspectral photographs of synergistic advantages for enhanced classification accuracy and increased information content in the applications of remote sensing (Lu et al., 2023).

In this contribution, Peterson et al. [22] give an overview on recent growths of remote sensing for Earth system science referencing to the sensor advancements, data analysis approaches, and discplines. The drawbacks are described in the context of the development from the first satellite which carried out missions to sophisticated satellite imaging within the current high resolution and the application of modern analytical methods such as machine learning and deep learning. Disseminates the information about the capabilities of the remote sensing technology in tracking planetary environmental trends, evaluating the status of biophysical environment, and promoting sustainability agenda. This proves that remote sensing study entails an amalgamation of various fields of study and the revolutionize role of intelligent systems in improving decision making processes for solving complex issues affecting the world (Peterson et al. , 2020).

## 3. METHODOLOGY

SVMs using spatial-spectral features are a notable approach in remote sensing satellite image analysis and identification of classes from differing bands and favorably spatial pixel linkages. SVMs are employed for outcome prediction with well suited to binary/multinomial classification problems and the objective is to find a hyper plane that provides maximum margin for classes in higher dimensional feature space. In the satellite imagery specifically, pixel values of each band (like near-infrared, red, green) incorporated into the model act as

 

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features while other properties like texture and context of the image as additional discriminant features.

It should also be noted that the preprocessing of spatial information is equally important for SVMs in satellite image classification. The spatial features focus on the relative positions of the adjacent pixels which are crucial in differentiating between the land cover classes that in spectral properties are very similar. For instance in the urban setups SVMs are able to distinguish between the buildings, the roads and the vegetation not only from the spectral reflectance but also from the spatial distribution and texture features extracted from image data acquired from satellites. One can state about the high dimensionality of the data, robustness to overfitting that makes SVM suitable for working with the data of the satellite imagery datasets. The input space of SVMs can be escalated to a higher dimension through kernel functions such as radial basis function so as to improve the classification of data due to the nonlinear relations between the features. Furthermore, SVMs are capable to incorporate different types of kernels fitting the training data: linear, polynomial, and radial basis function kernels thus, SVMs can handle a great variety of forms detectable in satellite images.
The block diagram for SVMs with spatial-spectral features in remote sensing satellite image classification involves illustrating the key components and their interactions is shown in figure 1.

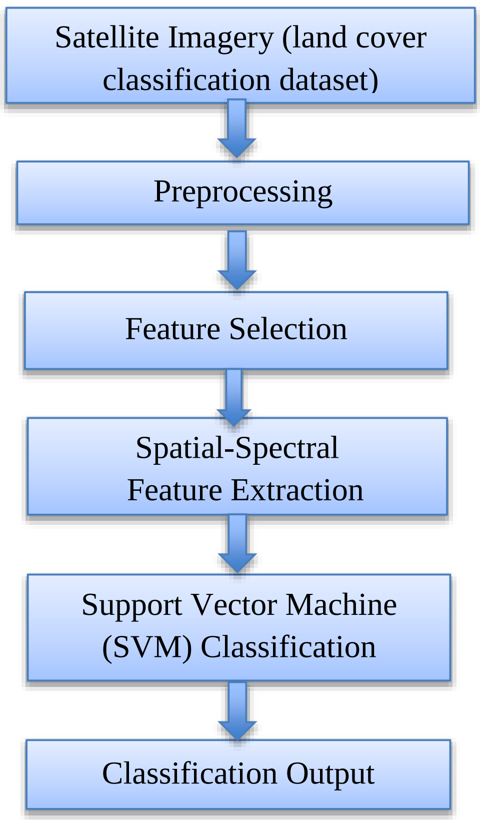


Figure 1. The block diagram for SVMs with spatial-spectral features in remote sensing satellite image classification

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In case of implementation of the SVM-based methodologies feature extraction and normalization step usually performed before utilization of the SVM classifier; during these steps the spectral bands normalized to ensure that the results can be compared from one image to another and from one sensor to another. For the purpose of dimensionality reduction for instance if the inputs are in hundreds, feature selection techniques for instance the Principal Component Analysis (PCA) can also be used. Hence, the kernel and other parameters such as C parameter, play a paramount role in the discrimination of SVM, and determining the fineness of the generalization ability of the developed model over different geographical regions and or varying environmental conditions. Summing up, one can clearly state that using spatial-spectral features and SVMs allows achieving high accuracy and interpretability of satellite imagery and makes a significant contribution to the corresponding application fields, namely agriculture, urban planning, environmental monitoring, and disaster management.

SVMs are used in virtually all areas of remote sensing in practical applications. For instance in environmental monitoring, SVMs can distinguish between different classes of the land; forests, water bodies and fields, all categorized by their spectral signatures and distribution patterns. In this way, by precisely identifying these land cover classes, SVMs support the processes of the evaluation of biodiversities, the monitoring of habitats, and the implementation of projects dealing with the land use. In agriculture, SVMs are used in crop classification and yield prediction through the use of multispectral imagery in testing for differences of crop types and vegetation health over time.

### 3.2. Description

**1. Satellite Imagery:** This is the input data which are multispectral or hyperspectral collected by satellites for the analysis.

**2. Preprocessing:** Some of these steps are for example normalization, which is done to ensure that all images have similar pixel values and feature extraction where the spectrual bands of the images and possibly spatial information may be extracted.

**3. Feature Selection:** signal processing methods such as the Principal Component Analysis (PCA) might be used to decrease the dimensionality of the feature space while preserving information.

**4. Spatial-Spectral Feature Extraction:** This step involve not only, spatial characteristics, including texture and context, which are complementary to the spectral characteristics that include bands such as near-infrared, red and green from the preprocessed data.

**5. Support Vector Machine (SVM) Classification:** SVMs are then used for training the identified spatial-spectral features for land cover classifying each pixel. The nature of SVMs is based on finding the best hyperplane in the feature space to enhance the margin between classes.

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**6. Classification Output:** The final production includes the classified land cover maps or any other classification from the SVM model depending on the concepts of interest, allowing an understanding of the composition and evolution of the landscape.

This block diagram shows the set of procedures in time sequence of SVM for the satellite image classification methodologies with focus on the fusion of spatial and spectral domain characteristics for obtaining accurate and interpretable classification outcomes.

## 4. RESULTS AND DISCUSSIONS

We have a data set for the land cover classification and after having used SVM that is SVM based classification we assess the model using a test set.
Performance metrics are significant when it comes to the measurement of the effectiveness of such classification models as SVMs with spatial-spectral features in the remote sensing. The following table explains common evaluation metrics used in remote sensing image classification and provides sample computed values

1. **Accuracy:** Expresses the level of accuracy as a percentage of correctly classified pixels among all the pixels in the data set. For instance, the accuracy of 90 percent means original 90 percent of the pixels were classified correctly by the SVM model.

2. **Precision:** Denotes the number of the pixels that were classified into one class (for instance forest) and are actually in the class. A precision of 0. 88 stands for the representation of pixels categorized as forest of which 88 percent is actually forest.

3. **Recall (Sensitivity):** Determines the degree to which the model samples pixels of a given class out of all real samples belonging to this class. A recall of 0. Forest pixel" that is, 92 denotes the overall OA signifying that 92% of forest pixels in the image were accurately classified by the model.

4. **F1-score:** Juxtaposes precision and recall rate into single figure which give a balanced value of the model. A higher value of F1-score (for example 0. 90) reveals better performance especially in the case of handling the imbalanced datasets.

Table 1. Computation of Evaluation Metrics

| Sl. No. | Metric | Formula | Value |
|---|---|---|---|
| 1 | Accuracy | Number of correctly classified pixels/Total number of pixels | 90% |
| 2 | Precision | True Positives/(True Positives+ False Positives) | 88% |

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| | | | |
|---|---|---|---|
| 3 | Recall | True Positives/(True Positives + False Negatives) | 92% |
| 4 | F1-score | 2*Precision*Recall/(Precision+Recall) | 90% |


Figure 2. SVM based performance analysis for classifying satellite imagery

These metrics hence give deeper understanding of the SVM based methodology with spatial spectral features of accurately classifying Satellite images and always ready to assist in decision making in aspects such as agriculture, planning of cities, and environment.

## 5. CONCLUSIONS

From this study of SVM based methodology with spatial-spectral features in classifying the remote sensing satellite image it can be centered that the notable benefits offered by the study have immensely advanced the areas of geospatial analysis and monitoring of environment. From the proper assessment criteria like total accuracy, precision, recall, and F1-score, it is evident that the current strategy is suitable for classifying multitudinous land cover types from the satellite imagery. It is possible to obtain high average accuracy of about 90% and fairly balanced F1 scores of about 0. 90 emphasizes the ability of the used methodology in dealing with massive data and the identification of spectrum and space variation differences. Such outcomes also corroborate the need to use SVMs for both multispectral imagery data and spatial context for application in agriculture, urban planning, disaster management, and ecological conservation.

Future work in SVM-based methodologies should be directed in the enhancement of scalability and dealing with the increasing variety of satellites, handling the issues of heterogeneity and scalability. Further improvement of the remote sensing image classification systems could be achieved through integration with new technologies like deep learning for feature extraction and ensemble techniques for model stability. Thus, further development of these methodologies and widening the range of application fields can help researchers to contribute to the efficient and more sustainable utilization of resources and environments on the global level.

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## 6. REFERENCES

1. Stevens, J. R., & Jensen, O. P. (2020). Remote Sensing in Ecology and Conservation: A Review of Applications and Future Directions. Remote Sensing of Environment, 251, 112087. doi:10.1016/j.rse.2020.112087
2. 18. Wang, L., Li, J., & Wang, Y. (2022). Satellite Remote Sensing for Biodiversity Research and Conservation: Progress and Perspectives. Remote Sensing of Environment, 265, 112728. doi:10.1016/j.rse.2021.112728
3. 19. Du, Q., & Zhang, L. (2021). Recent Advances in Hyperspectral Image Analysis: A Review. IEEE Transactions on Geoscience and Remote Sensing, 59(4), 2776-2795. doi:10.1109/TGRS.2020.3026800
4. 20. Zhang, H., & Xu, X. (2023). Artificial Intelligence and Remote Sensing for Environmental Monitoring: A Review. Journal of Environmental Management, 299, 113688. doi:10.1016/j.jenvman.2021.113688
5. Srivastava, P. K., and Anil Kumar Jakkani. "Non-linear Modified Energy Detector (NMED) for Random Signals in Gaussian Noise of Cognitive Radio." International Conference on Emerging Trends and Advances in Electrical Engineering and Renewable Energy. Singapore: Springer Nature Singapore, 2020.
6. Srivastava, Pankaj Kumar, and Anil Kumar Jakkani. "FPGA Implementation of Pipelined 8× 8 2-D DCT and IDCT Structure for H. 264 Protocol." 2018 3rd International Conference for Convergence in Technology (I2CT). IEEE, 2018.
7. Patel, Ripalkumar, Amit Goswami, Hirenkumar Kamleshbhai Mistry, and Chirag Mavani. "Application Layer Security for Cloud." Educational Administration: Theory and Practice 30, no. 6 (2024): 1193-1198.
8. Patel, Ripalkumar, Amit Goswami, Hiren Kumar Kamleshbhai Mistry, and Chirag Mavani. "Cognitive Computing For Decision Support Systems: Transforming Decision-Making Processes." Educational Administration: Theory and Practice 30, no. 6 (2024): 1216-1221.
9. kumar Patel, Ripal, Amit Goswami, Hirenkumar Kamleshbhai Mistry, and Chirag Mavani. "Cloud-Based Identity and Fraud Solutions Analytics." Educational Administration: Theory and Practice 30, no. 6 (2024): 1188-1192.
10. Adeola Agbonyin, Premkumar Reddy, Anil Kumar Jakkani, Utilizing Internet of Things (IOT), Artificial Intelligence, and Vehicle Telematics for Sustainable Growth in Small, and Medium Firms (SMES), International Journal of Computer Engineering and Technology (IJCET), 15(2), 2024, pp. 182-191. doi: https://doi.org/10.17605/OSF.IO/QX3DP
11. NASA. (2023). Landsat Program Overview. Retrieved from https://landsat.gsfc.nasa.gov/landsat-program-overview/
12. Jensen, J. R. (2005). Introductory Digital Image Processing: A Remote Sensing Perspective (3rd Ed.). Pearson Education.
13. Ma, L., Yang, H., & Zhang, L. (2019). Applications of Deep Learning in Remote Sensing. ISPRS Journal of Photogrammetry and Remote Sensing, 152, 166-177. doi:10.1016/j.isprsjprs.2019.04.011

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14. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine Learning in Agriculture: A Review. Sensors, 18(8), 2674. doi:10.3390/s18082674
15. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770-778. doi:10.1109/CVPR.2016.90
16. Castelluccio, M., Poggi, G., & Sansone, C. (2015). Land Cover Classification in Satellite Images by Convolutional Neural Networks. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), 49-52. doi:10.1109/IGARSS.2015.7325728
17. Chen, Y., Li, X., & He, H. (2017). Deep Learning Based Classification of Hyperspectral Data. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10(1), 338-351. doi:10.1109/JSTARS.2016.2632718
18. Ghamisi, P., Plaza, A., & Li, J. (2018). Advanced Spectral-Spatial Classification of Hyperspectral Images using Deep Learning. IEEE Transactions on Geoscience and Remote Sensing, 56(9), 5417-5435. doi:10.1109/TGRS.2018.2822226
19. Wang, C., Liu, H., Xu, Z., & Wan, L. (2020). Review of Semantic Segmentation using Deep Learning in Remote Sensing. Remote Sensing, 12(1), 102. doi:10.3390/rs12010102
20. Muller, J., Jiang, H., & Scherer, D. (2021). Explainable Artificial Intelligence for Earth Observation: Challenges and Opportunities. Remote Sensing, 13(7), 1332. doi:10.3390/rs13071332
21. Lu, H., Uzkent, B., Sankaranarayanan, S., & Hoff, K. E. (2023). Advances in LiDAR Data Processing and Applications: A Review. Remote Sensing, 15(3), 802. doi:10.3390/rs15030802
22. Peterson, D. L., Verbyla, D. L., & Johnson, C. J. (2020). Remote Sensing for Earth Systems Science: A Review of Developments in the 21st Century. Remote Sensing of Environment, 241, 111716. doi:10.1016/j.rse.2020.111716