© January 2025 | IJIRT | Volume 11 Issue 8 | ISSN: 2349-6002

Comparative Analysis on Satellite Imagery Classification and Object Segmentation Based on Computer Vision and Artificial Intelligence

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***Abstract*—Satellite imaging has become an essential tool for observing the Earth's surface, facilitating many uses including urban growth, environmental preservation, and disaster response. The escalating amount and resolution of satellite imagery need the development of efficient and precise methodologies for image classification and object segmentation. This study offers a comparative review of several Computer Vision (CV) and Artificial Intelligence (AI) methodologies for the classification and segmentation of satellite data. The exploration encompasses various traditional machine learning methods alongside advanced deep learning techniques, including Convolutional Neural Networks (CNNs), U-Net, and Vision Transformers. Performance criteria like as accuracy, Intersection over Union (IoU), and F1 score are employed to assess these algorithms on benchmark datasets. The research delineates the advantages and drawbacks of each methodology, offering insights into their relevance for certain applications in satellite image analysis.**

***Index Terms*—Remote Sensing, Artificial Intelligence, Satellite Imagery, Deep Learning, Machine Learning**.

I. INTRODUCTION

Satellite imaging has emerged as a crucial instrument in several fields, including environmental monitoring, agricultural management, urban development and disaster response. Advancements in remote sensing technology have markedly enhanced the quality and accessibility of high-resolution satellite imagery [1-4]. These images offer significant insights for monitoring alterations in land use, identifying items, and tracking environmental events across extensive geographical regions [5][7]. Nonetheless, the intricate, extensive, and multi-faceted characteristics of satellite data render the successful extraction of valuable insights a considerable problem. Artificial Intelligence (AI) and Computer Vision (CV) approaches are crucial in this context [9-12].

In recent years, AI and Deep Learning (DL) models, particularly Convolutional Neural Networks (CNN), have transformed the domain of image analysis. CNNs are especially adept in processing spatial data, including image classification and segmentation, owing to their capacity to autonomously learn and extract hierarchical features from unprocessed image data [15-18]. In addition to CNNs, specific architectures like as U-Net have developed for image segmentation tasks, offering effective solutions for object recognition and localization [21][23][29]. Recently, Vision Transformers (ViTs) have garnered attention for their capacity to capture global dependencies in pictures, positioning them as a viable alternative to CNN-based models in satellite image analysis [32-34][37-38]. This paper aims to compare these various techniques in terms of performance, efficiency, and scalability when applied to satellite imagery for classification and object segmentation tasks. Also, this paper aims to answer key questions regarding the efficacy of traditional machine learning and modern deep learning techniques in satellite imagery analysis. The focus is on determining the optimal approaches for specific tasks, identifying the strengths and weaknesses of different models, and providing insights into the future directions for research and development in this rapidly evolving field. The main contributions of the paper are:

- Provided an overview of benchmark remote sensing satellite and aerial image datasets.
- Compared the summary of the properties and performance of the reviewed methods for object segmentation and classification purposes, on popular benchmarks.

- Discussed several challenges and potential future directions for deep learning-based image segmentation.

The remainder of this paper is arranged as follows: Section 2 briefly discusses the work in the literature, section 3 overviewed the standard benchmark datasets used. Section 4 introduces the generalized methodology, and Section 5 discusses the achieved comparative results evaluation of existing research. Finally, section 6 concludes the paper.

II. RELATED WORK

Numerous research has investigated the application of ML and DL methodologies for the classification and segmentation of satellite imagery. Conventional methods of classical ML have been extensively employed owing to their simplicity and efficacy with smaller datasets. Nevertheless, as the complexity and scale of satellite imaging datasets have expanded, these conventional approaches have demonstrated inadequacies in their capacity to capture intricate details and higher-dimensional characteristics. Deep learning, especially CNNs, has emerged as the preeminent method in satellite image analysis owing to its capacity to autonomously learn and extract information from pictures. The U-Net architecture, developed for image segmentation, has demonstrated considerable advancements in segmenting satellite pictures while maintaining spatial hierarchies. Vision Transformers, while being relatively novel, have exhibited encouraging outcomes in classification and segmentation tasks, utilizing their capacity to collect global context in pictures [1-5]. This study further examines the current research on classification-based and object segmentation-based approaches for their use in various contexts.

A. Classification-based Approach

The OPS-SAT pictures dataset explores the interplay between data and model-centric methodologies, highlights the need of generating synthetic training data, and shows the benefits of ensemble learning [6]. Satellite image categorization is conducted according to their topologies and geographical characteristics utilizing various ML and DL techniques [8]. The assessment and study of DL methodologies utilizing CNN and Vision Transformer for the effective categorization of remote sensing satellite pictures are provided [10]. CNN architecture employing a scaling mechanism is presented for the categorization of satellite pictures, facilitating an end-to-end, scalable interpretation that categorizes them into four distinct groups [13]. Typhoon-CNNs framework is an automated classifier for typhoon strength that employs CNN with a cyclical convolution technique enhanced with dropout zero-set, which identifies critical aspects of existing spiral cloud bands [14]. A method proposed for executing object classification and segmentation in satellite imagery inside the Maritime domain utilizing neural network architectures for these tasks [30]. ML-based technique was proposed for ship detection and performance estimation using pan-sharpened optical pictures with a resolution of 0.55 meters from KOMPSAT-3A [31]. A specialized approach proposed for the detection and identification of airplanes utilizing modified U-Net and RetinaNet architectures [35].

B. Object Segmentation-based Approach

Diverse techniques have been devised to identify buildings in satellite imagery utilizing deep learning through CNN [19]. The semantic representation is employed to collect the semantic areas of downscaled pictures utilizing a deep neural forest classifier [20]. An entirely CNN architecture optimized for precise and expedited object detection in multispectral satellite images [22]. DL segmentation architecture has been presented that integrates the properties of MobileNet and U-Net architectures, yielding segmentation results with high accuracy [24]. U-HardNet introduced an innovative activation function termed Hard-Swish for the segmentation of remotely sensed pictures [25]. A deep convolutional U-Net architecture was presented that employs transfer learning for the semantic segmentation of clouds in satellite images [26]. A technique for semantic segmentation of remote sensing pictures utilizing CNN and mask creation is proposed [27]. The satellite imaging collection was developed for object detection with CNN-based frameworks, SIMRDWN [28]. Fuzzy Neural Network (FNN) traffic evaluation approach is suggested, utilizing optical high-resolution Remote Sensing Imagery (RSI) to analyze a non-quantified correlation between traffic data and the assessment outcome [38].

II. BENCHMARK DATASETS

In satellite and aerial image classification, several benchmark datasets are utilized for the training and assessment of machine learning and deep learning models. These datasets include a variety of images obtained from satellites and aerial platforms, crucial for applications such land cover categorization, urban area segmentation, object recognition, and environmental monitoring. The following are some of the most commonly utilized benchmark datasets in this field [2][4-5][10][12]:

Table 1: Overview of Benchmark Datasets

Datasets	Size	Classes	Resolution	Source	Objects
DOTA	2806	15	Varies	Multiple Aerial Image	Airplanes, Ships, Vehicles, And More.
xView	1 million object instances	60	30cm	DigitalGlobe	Buildings, Vehicles, And Various Other Object Classes.
SpaceNet	24,586	-	30cm	DigitalGlobe	Buildings, Roads, And Other Man-Made Structures.
AID	10,000	30	600x600 pixels	Google Earth	Various Scenes Such as Airports, Bridges, And Parking Lots.
UC Merced Land Use	2100	21	256x256 pixels	UC Merced	Agricultural, Residential, Commercial, and Other Land Use Classes.
Indian Pines	224 Bands	16	20 meters per pixel	Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) Sensor	Various Types of Vegetation, Soil, And Man-Made Structures
Pavia University	103 Bands	9	1.3 meters per pixel	Reflective Optics System Imaging Spectrometer (ROSIS)	Buildings, Roads, Trees, And Shadows
Salinas	224 Bands	16	3.7 meters per pixel	AVIRIS Sensor	Vegetation, Bare Soils, and Vineyard Fields.
Botswana	242 Bands	14	30 meters per pixel	Hyperion Sensor	Various Types of Vegetation and Water Bodies.

IV. METHODOLOGY

The methodology for comparative Analysis on Satellite Imagery Classification and Object Segmentation based on CV and AI can be broken down into the following generalized steps and shown in figure 1.

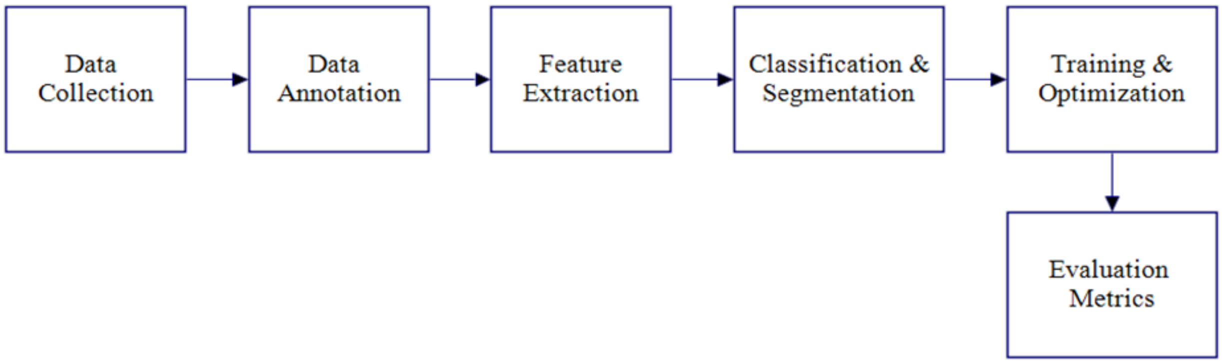

Figure 1: Generalized Methodological Approach for Satellite Imagery Classification and Segmentation

A. Data Collection

Dataset Selection: A diverse selection of satellite and aerial picture datasets is chosen, comprising high-resolution optical, infrared, and multi-spectral imaging. These datasets frequently include annotations for object recognition, classification, and segmentation tasks.

Preprocessing: The gathered datasets undergo pre-processing to assure uniformity and quality. This comprises picture resizing, normalization, and data augmentation methods (e.g., rotation, flipping, scaling) to improve the variety of training samples and mitigate overfitting.

B. Data Annotation

Labeling: Each dataset employs suitable labels to classify the photographs into categories or to identify the things included inside. Segmentation tasks need pixel-level annotations, whereas classification tasks concentrate on identifying whole pictures or areas.

Class Imbalance Handling: Due to the frequent class imbalance in satellite pictures (e.g., a predominance of urban regions over rural areas), methodologies such as oversampling, undersampling, or the Synthetic Minority Over-sampling Technique (SMOTE) are employed to equilibrate the dataset.

C. Feature Extraction

Convolutional Neural Networks (CNNs): CNNs are utilized to extract hierarchical features from pictures, including spatial patterns, textures, and edges. Feature maps produced by different CNN layers function as input for classification or segmentation tasks.

Pretrained Models: Pretrained deep learning models (e.g., ResNet, EfficientNet) are refined on satellite image datasets to utilize their capacity for feature generalization, especially in contexts with few labeled data.

D. Model Architectures

Classification Models: Several machine learning and deep learning architectures are implemented, such as Random Forest (RF)**,** Support Vector Machines (SVMs)**,** Convolutional Neural Networks (CNNs).

Segmentation Models: Segmentation tasks are performed using U-Net, a specific deep learning model for picture segmentation that enables pixel-wise classification while maintaining spatial resolution. Fully Convolutional Networks (FCNs) are employed for dense prediction tasks, particularly suited for semantic segmentation in satellite data. Vision Transformers (ViTs) are utilized to capture long-range dependencies in pictures, effectively executing both classification and segmentation tasks.

E. Training and Optimization

Model Training: The models are trained with processed satellite and aerial imagery. Methods include batch normalization, cross-validation, and dropout are utilized to mitigate overfitting.

Optimization Algorithms: Optimizers such as SGD (Stochastic Gradient Descent), Adam, and RMSProp are employed to minimize the loss function (e.g., cross-entropy for classification, dice loss for segmentation).

Hyperparameter Tuning: Grid search and random search are employed for hyperparameter optimization, including learning rate, batch size, and layer count, to identify the ideal configuration for each model.

F. Evaluation Metrics

The performance of each model is compared across different datasets and metrics, identifying the strengths and weaknesses of each approach.

Classification Metrics*:* Accuracy, precision, recall, and F1-score are used to evaluate the performance of classification models.

Segmentation Metrics*:* Intersection over Union (IoU), Dice coefficient, and pixel-wise accuracy are used to evaluate segmentation models.

V. COMPARATIVE RESULT ANALYSIS

This section presents an overview of prevalent metrics utilized for assessing the performance of picture classification and object segmentation models, along with the quantitative performance of notable ML and DL models on well recognized datasets, as shown in Tables 2 and 3.

Table 2: Evaluation Summary of Existing Model for Imagery Classification

References	Datasets	Classes	Methodology	Results Evaluation
R. Shendy et.al. [6]	OPS-SAT	8	Deep Learning Model, EfficientNetLite-B0	Accuracy – 50.62, Scoring Metric – 0.86
D. Yadav et.al. [8]	EuroSAT	10	GoogleNet	Accuracy - 99.68%, Precision - 99.42%, Recall - 99.51%, F-Score - 99.45%
A. A. Adegun et.al. [10]	UCMerced-LandUse	21	DenseNet121	Accuracy - 98%, Precision - 98%, Recall - 98%, F-Score - 98%
A. A. Adegun et.al. [10]	NWPU-RESISC45	45	DenseNet121	Accuracy - 98%, Precision - 98%, Recall - 98%, F-Score - 98%
S. Tehsin et.al. [13]	RSI-CB256	4	EfficientNet B7	Accuracy – 99.6%, Precision – 99.7%, Recall – 99.7%, F-Score – 99.7%
Z. Zheng et.al. [14]	Typhoon	5	Typhoon-CNNs	Accuracy – 88.74%
K. Berata et.al. [30]	Sentinel-2 Maritime	5	Vanilla Mini CNN-UNet	Accuracy – 99%
J. Y. Chang et.al. [31]	KOMPSAT-3A (Ship)	1	AdaBoost	Precision – 78.2%, Recall – 78.7%.
D. Grosgeorge et.al. [35]	Aircraft (‘bomber’, ‘civilian’, ‘combat’, ‘drone’, ‘special’ and ‘transport’)	6	modified U-net	Precision – 84%, Recall – 96%

Table 3: Evaluation Summary of Existing Model for Object Segmentation

References	Datasets	Object	Methodology	Results Evaluation
S. P. Mohanty et.al. [15]	SpaceNet	Building	U-Net and Mask R-CNN	Average Precision – 93.7%, Average Recall – 95.9%
A. Femin et.al. [19]	Google Earth	Building	CNN	Accuracy – 83%

Y. H. Robinson et.al. [20]	NWPU-VHR-10	Airplanes, Bridges, Harbors, Ground Track Feilds, Basketball Courts, Tennis Courts, Buildings, Trees, Ships, Cars.	Tree-CNN	Accuracy – 96.5%, Precision – 97.2%, Recall – 93.8%, F-Score – 94.2%
P. Gudzius et.al. [22]	SpaceNet	Building	U-Net Fully Convolutional Neural Network (FCN)	Accuracy – 97.67%
M. A. Wani et.al. [24]	Duke CaliforniaSolar array dataset (DCSA)	Solar Array	Mobilenet and U-Net	Precision – 95.95%, Recall – 84.98%, DSC – 90.94%
R. Avenash et.al. [25]	DSTL (Defence Science and Technology Laboratory)	Building, Structure, Road, Track, Trees, Crops, Waterway, Standing Water, Vehicle Large and Small	U-HardNet	Accuracy – 97.75%
C. Gonzales et.al. [26]	38-Cloud - Landsat 8	Cloud	Deep Convolutional U-Net	Accuracy – 95.81%, Precision – 86.19%, Recall – 88.14%, Specificity – 99.04%,
B. Niu et.al. [27]	Vaihingen	Low Vegatation, Buildings, Impervious Surfaces, Cars, Trees	CNN and Mask Generation	Precision – 89.9%, Recall – 91.4%, IoU – 82.7%
A. Tahir et.al. [28]	Google Earth	Aircrafts	SIMRDWN (satellite imagery multiscale rapid detection with windowed networks)	Accuracy – 97%
T. Gupta et.al. [36]	Natural Disasters	Volcanic Eruption, Hurricane, Flood,	LBP and Wavelet Image Scattering Features	Accuracy – 99.59%, F-score – 99.40%

		Earthquake, Tsunami and Wildfire		
X. Ma et.al. [39]	PLANET	Wildfire	Flips + SSR + HSV_dist	Precision – 0.295, Recall – 0.356, F1score – 0.321.

The efficacy of each strategy was assessed across diverse datasets with differing complexities and resolutions. CNNs and U-Net regularly surpassed conventional ML techniques, especially in managing extensive and intricate datasets. CNNs shown significant efficacy in the categorization of satellite imagery, with elevated accuracy metrics across several datasets. U-Net, engineered for segmentation tasks, shown exceptional proficiency in delineating things such as edifices and thoroughfares in high-resolution imagery. Vision Transformers, despite their computational intensity, shown enhanced performance on extensive datasets, especially in recognizing long-range spatial connections. Nonetheless, they necessitate greater processing resources, hence constraining their use in real-time applications or environments with restricted hardware capabilities.

VI. CONCLUSION

This research presents a thorough comparative assessment of several ML and DL techniques for satellite image classification and object segmentation. Deep learning models, notably CNNs and U-Net, surpass conventional ML algorithms in the majority of instances, particularly with extensive and intricate datasets. Vision Transformers, however yielding promising outcomes, need substantial processing resources, rendering them less feasible for real-time or resource-limited applications. The findings underscore the compromises among precision, computational expense, and generalizability across various models. Future endeavours may benefit from the inclusion of hybrid models that amalgamate the advantages of classical and deep learning approaches, perhaps resulting in enhanced performance. Moreover, the advancement of more efficient transformer-based models may diminish their computational demands, hence enhancing their applicability across an expanded range of uses.

REFERENCES

[1] Li, Jiangyun, Yuanxiu Cai, Qing Li, Mingyin Kou, and Tianxiang Zhang. 2024. “A Review of Remote Sensing Image Segmentation by Deep Learning Methods.” International Journal of Digital Earth 17 (1). doi:10.1080/17538947.2024.2328827.

[2] Miller, Lynn & Pelletier, Charlotte & Webb, Geoffrey. (2024). Deep Learning for Satellite Image Time-Series Analysis: A review. IEEE Geoscience and Remote Sensing Magazine. PP. 2-45. 10.1109/MGRS.2024.3393010.

[3] Amer, Ibrahim & Rahouma, Kamel & Shahin, Attia. (2024). Remote sensing Image processing, DEEP learning Classification algorithms survey and review. Journal of Applied Engineering & Technology (JAET). 43. 239.

[4] Mo, S., Shi, Y., yuan, Q., & Li, M. (2024). A Survey of Deep Learning Road Extraction Algorithms Using High-Resolution Remote Sensing Images. Sensors (Basel, Switzerland), 24(5). https://doi.org/10.3390/s24051708.

[5] Mohanty, A., Gao, G. A survey of machine learning techniques for improving Global Navigation Satellite Systems. EURASIP J. Adv. Signal Process. 2024, 73 (2024). https://doi.org/10.1186/s13634-024-01167-7.

[6] Shendy, R., & Nalepa, J. (2024). Few-shot satellite image classification for bringing deep learning on board OPS-SAT. Expert Systems with Applications, 251, 123984. https://doi.org/10.1016/j.eswa.2024.123984.

[7] Yasin, Emad & Kornel, Czimber. (2024). Evaluating Satellite Image Classification: Exploring Methods and Techniques. 10.5772/intechopen.1003196.

[8] Yadav, D., Kapoor, K., Yadav, A.K. et al. Satellite image classification using deep learning approach. Earth Sci Inform 17, 2495–2508

(2024). https://doi.org/10.1007/s12145-024-01301-x.

[9] Talebi, H., Samadianfard, S. & Kamran, K.V. Investigating the roles of different extracted parameters from satellite images in improving the accuracy of daily reference evapotranspiration estimation. Appl Water Sci 13, 59 (2023). https://doi.org/10.1007/s13201-022-01862-6.

[10] Adegun, A.A., Viriri, S. & Tapamo, JR. Review of deep learning methods for remote sensing satellite images classification: experimental survey and comparative analysis. J Big Data 10, 93 (2023). https://doi.org/10.1186/s40537-023-00772-x.

[11] Soufi, O., & Belouadha, F. Z. (2023). Enhancing Accessibility to High-Resolution Satellite Imagery: A Novel Deep Learning-Based Super-Resolution Approach. Journal of Environmental Treatment Techniques, 11(2), 44-49. https://doi.org/10.47277/JETT/11(2)61.

[12] Cheng, X., Sun, Y., Zhang, W., Wang, Y., Cao, X., & Wang, Y. (2022). Application of Deep Learning in Multitemporal Remote Sensing Image Classification. Remote Sensing, 15(15), 3859. https://doi.org/10.3390/rs15153859.

[13] Tehsin, S., Kausar, S., Jameel, A., Humayun, M., & Almofarreh, D. K. (2022). Satellite Image Categorization Using Scalable Deep Learning. Applied Sciences, 13(8), 5108. https://doi.org/10.3390/app13085108.

[14] Zheng, Zongsheng, Chenyu Hu, Zhaorong Liu, Jianbo Hao, Qian Hou, and Xiaoyi Jiang. "Deep Learning for Typhoon Intensity Classification Using Satellite Cloud Images". Journal of Atmospheric and Oceanic Technology 39.1 (2022): 55-69. https://doi.org/10.1175/JTECH-D-19-0207.1 Web.

[15] Minaee, Shervin & Boykov, Yuri & Porikli, Fatih & Plaza, Antonio & Kehtarnavaz, Nasser & Terzopoulos, Demetri. (2021). Image Segmentation Using Deep Learning: A Survey. IEEE transactions on pattern analysis and machine intelligence. PP. 10.1109/TPAMI.2021.3059968.

[16] Mohanty, Sharada & Czakon, Jakub & Kaczmarek, Kamil & Pyskir, Andrzej & Tarasiewicz, Piotr & Kunwar, Saket & Rohrbach, Janick & Luo, Dave & Prasad, Manjunath & Fleer, Sascha & Göpfert, Jan & Tandon, Akshat & Mollard, Guillaume & Rayaprolu, Nikhil & Salathe, Marcel & Schilling, Malte. (2020). Deep Learning for Understanding Satellite Imagery: An Experimental Survey. Frontiers in Artificial Intelligence. 3. 10.3389/frai.2020.534696.

[17] Hoeser, T., & Kuenzer, C. (2020). Object Detection and Image Segmentation with Deep Learning on Earth Observation Data: A Review-Part I: Evolution and Recent Trends. Remote Sensing, 12(10), 1667. doi:10.3390/rs12101667

[18] Hoeser, Thorsten, Felix Bachofer, and Claudia Kuenzer. 2020. "Object Detection and Image Segmentation with Deep Learning on Earth Observation Data: A Review—Part II: Applications" Remote Sensing 12, no. 18: 3053. https://doi.org/10.3390/rs12183053

[19] A. Femin and K. S. Biju, "Accurate Detection of Buildings from Satellite Images using CNN," 2020 International Conference on Electrical, Communication, and Computer Engineering (ICECCE), 2020, pp. 1-5, doi: 10.1109/ICECCE49384.2020.9179232.

[20] Robinson, Harold & Shanmuganthan, Vimal & Khari, Manju & Lopez Hernandez, Fernando & Gonzalez Crespo, Ruben. (2020). Tree-based Convolutional Neural Networks for Object Classification in Segmented Satellite Images. International Journal of High-Performance Computing Applications. IP. 25. 10.1177/1094342020945026.

[21] Ibrahim Goni, Asabe Sandra Ahmadu, Yusuf Musa Malgwi, Multi-class Object Detection Model in Satellite Images Using Convolutional Neural Network, Communications. Vol. 9, No. 1, 2021, pp. 1-5. doi: 10.11648/j.com.20210901.11

[22] Gudžius, Povilas & Kurasova, Olga & Darulis, Vytenis & Filatovas, Ernestas. (2021). Deep learning-based object recognition in multispectral satellite imagery for real-time applications. Machine Vision and Applications. 32. 10.1007/s00138-021-01209-2.

[23] Ulmas, Priit and Innar Liiv. “Segmentation of Satellite Imagery using U-Net Models for Land Cover Classification.” ArXiv abs/2003.02899 (2020): n. pag.

[24] Mujtaba, Tahir & Wani, M. (2021). Segmentation of Satellite Images of Solar Panels Using Fast Deep Learning Model.

[25] Avenash, R. and Prashanth Viswanath. "Semantic Segmentation of Satellite Images using a Modified CNN with Hard-Swish Activation Function." VISIGRAPP (2019).

[26] C. Gonzales, W. A. Sakla, "Semantic Segmentation of Clouds in Satellite Imagery Using Deep Pre-Trained U-Nets"

[27] Binglin Niu, "Semantic Segmentation of Remote Sensing Image Based on Convolutional Neural Network and Mask Generation", Mathematical Problems in Engineering, vol. 2021, Article ID 2472726, 13 pages, 2021. https://doi.org/10.1155/2021/2472726

[28] Tahir, Arsalan, Hafiz Suliman Munawar, Junaid Akram, Muhammad Adil, Shehryar Ali, Abbas Z. Kouzani, and M. A. Parvez Mahmud. 2022. "Automatic Target Detection from Satellite Imagery Using Machine Learning" Sensors 22, no. 3: 1147. https://doi.org/10.3390/s22031147.

[29] Bandarupally, Harika & Talusani, Harshitha & Sridevi, T. (2020). Detection of Military Targets from Satellite Images using Deep Convolutional Neural Networks. 531-535. 10.1109/ICCCA49541.2020.9250864.

[30] Bereta, Konstantina & Zissis, Dimitris & Grasso, Raffaele. (2020). Automatic Maritime Object Detection Using Satellite imagery. 1-5. 10.1109/IEEECONF38699.2020.9389431.

[31] Chang, Jae & Oh, Han & Lee, Seung-Jae & Lee, Kwang. (2020). Ship Detection for KOMPSAT-3A Optical Images Using Binary Features and Adaboost Classification. 968-971. 10.1109/IGARSS39084.2020.9323847.

[32] Chaurasia, Kuldeep & Nandy, Rijul & Singh, Ravi & Ahire, Meghana. (2021). Semantic segmentation of high-resolution satellite images using deep learning. Earth Science Informatics. 14. 1-10. 10.1007/s12145-021-00674-7.

[33] K. Yuan, X. Zhuang, G. Schaefer, J. Feng, L. Guan and H. Fang, "Deep-Learning-Based Multispectral Satellite Image Segmentation for Water Body Detection," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 7422-7434, 2021, doi: 10.1109/JSTARS.2021.3098678.

[34] S. Drouyer, "VehSat: a Large-Scale Dataset for Vehicle Detection in Satellite Images," IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, 2020, pp. 268-271, doi: 10.1109/IGARSS39084.2020.9323289

[35] Grosgeorge, Damien & Arbelot, Maxime & Goupilleau, Alex & Ceillier, Tugdual & Allioux, Renaud. (2020). Concurrent Segmentation and Object Detection CNNs for Aircraft Detection and Identification in Satellite Images. 276-279. 10.1109/IGARSS39084.2020.9323338.

[36] Gupta, Tanu & Roy, Sudip. (2020). A Hybrid Model based on Fused Features for Detection of Natural Disasters from Satellite Images. 1699-1702. 10.1109/IGARSS39084.2020.9324611.

[37] Huang, Chau-Lin & Munasinghe, Thilanka. (2020). Exploring Various Applicable Techniques to Detect Smoke on the Satellite Images. 5703-5705. 10.1109/BigData50022.2020.9378466.

[38] X. Ma, X. Hao and H. Chen, "Fuzzy Neural Network-Based Assessment of Road Traffic Situations Using Extracted Information Obtained from Optical High-Resolution Satellite Remote Sensing Images," IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, 2020, pp. 148-151, doi: 10.1109/IGARSS39084.2020.9323452.

[39] V. Khryashchev and R. Larionov, "Wildfire Segmentation on Satellite Images using Deep Learning," 2020 Moscow Workshop on Electronic and Networking Technologies (MWENT), 2020, pp. 1-5, doi: 10.1109/MWENT47943.2020.9067475.