A Machine Learning Approach for Object Detection in Satellite Images

Aaditya Kumrawat[1], Prof. Pankaj Raghuwanshi[2]

Abstract: Machine Learning (ML) and Deep Learning (DL) have revolutionized various fields, and satellite object detection is no exception. By enabling the automatic identification and classification of objects in satellite imagery, such techniques have significantly improved the efficiency and accuracy of remote sensing applications. From monitoring environmental changes to urban planning and disaster management, machine learning enabled satellite object detection plays a critical role in modern geospatial analysis**.** This paper proposes an approach comprising of segmentation, feature extraction and neural network based pattern recognition for satellite object detection. The deconvolution algorithm has been employed for noise removal followed by maximal gradient based segmentation prior to pattern recognition using a deep neural network structure. The performance of the proposed approach is the classification accuracy which is found to be higher compared to exiting work in the domain.

Keywords—Satellite Object Detection, Machine Learning, Deep Learning, Iange Pre-Processing, Classificaiton Accuracy.

I. INTRODUCTION

Machine Learning and Deep Learning algorithms have brought about a paradigm shift in the domain of satellite object detection. Satellite object detection has become a critical component of modern technology, enabling the identification and analysis of objects in satellite imagery [1]. With advancements in imaging systems and data processing, the need for satellite object detection has grown significantly. This technology is instrumental in addressing challenges related to environmental monitoring,

urban planning, disaster management, and global security [2]. This has resulted in the growing satellite

encies and private firms [3].

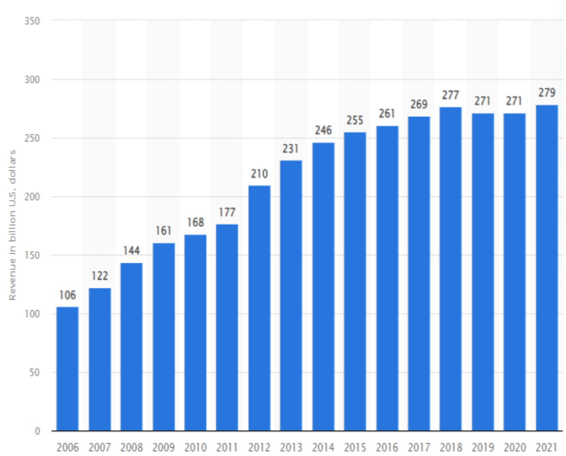

Fig.1 Evolving Revenue Statistics for Satellite Industry

Figure 1 depicts the evolving revenue statistics for satellite industry which is seeing a steady increase year after year [4]. The satellite industry has experienced unprecedented growth over the past few decades, driven by technological advancements, increasing demand for connectivity, and the need for geospatial data [5]. This growth has transformed the sector into a critical enabler of global communication, navigation, and observation [6]. From commercial ventures to governmental initiatives, the satellite industry has become a cornerstone of modern infrastructure and innovation [7].

One of the primary factors contributing to the growth of the satellite industry is the rapid advancement in technology [8]. Miniaturization of components, improvements in propulsion systems, and the development of reusable rockets have significantly reduced the cost of satellite launches [9]. Technologies like high-throughput satellites (HTS), advanced sensors, and artificial intelligence have further enhanced the capabilities of satellites, making them more efficient and versatile [10].

II. MACHINE LEARNING ENABLED SATELLITE OBJECT DETECTION

Satellite object detection involves identifying and classifying objects such as buildings, vehicles, roads, and natural features (e.g., forests, rivers) from satellite images. This task is crucial for addressing global challenges, including climate change, deforestation, and rapid urbanization [11]. Traditional manual analysis of satellite imagery is time-consuming and prone to errors, making ML essential for automating and scaling these processes. By providing faster and more accurate insights, ML has transformed satellite image analysis into a valuable tool for decision-making across industries [12].

Various ML techniques are employed for satellite object detection, including supervised learning, unsupervised learning, and deep learning [13] Supervised learning relies on labeled datasets to train algorithms, while unsupervised learning explores patterns in unlabeled data. Deep learning such as neural networks has emerged as the most effective approach for object detection in satellite images [14]. Deep net excel at extracting spatial features from high-resolution imagery, enabling precise detection of complex objects [15]. Techniques such as image enhancement, noise reduction, and geometric corrections are applied to ensure that the data is clean and ready for analysis. Annotated datasets, which provide ground-truth labels, are also vital for training supervised models [16].

ML-powered satellite object detection has diverse applications across sectors. In agriculture, it is used to monitor crop health and optimize resource allocation. In urban planning, it helps map infrastructure and assess land use patterns. In disaster management, it facilitates real-time detection of damage and aids in resource deployment. Additionally, defense and security applications include border monitoring and surveillance [17]. The versatility of ML in satellite object detection demonstrates its potential to address various real-world problems. Despite its advantages, satellite object detection using ML faces several challenges [18]. High-resolution satellite images often contain noise, clouds, and shadows that can hinder accurate detection. Furthermore, the need for large, annotated datasets can be a bottleneck, especially for supervised learning models. Variability in image quality, geographic regions, and object scales also poses difficulties for generalizing ML models. Finally, computational requirements for training and deploying deep learning models can be resource-intensive [19]

III. METHODOLOGY

The proposed methodology comprises of three major segmentation

1. Pre-Processing
2. Feature Extraction
3. Pattern Recognition

Each of the sections is presented next:

Pre-Processing:

The pre-processing section comprises of noise removal and segmentation.

Typically, satellite images are noisy in nature. Hence denoising is needed. Noise in satellite images can obscure important details, making it difficult to extract meaningful information. For instance, random noise can affect the clarity of features such as roads, buildings, or vegetation. Denoising is essential to enhance the quality of images and ensure accurate analysis for applications. Effective denoising techniques help improve the signal-to-noise ratio while preserving critical details. The deconvolution algorithm computes the deconvolution on noise effects as:

$$\boldsymbol{D} = [\boldsymbol{conv}(\boldsymbol{g}, \boldsymbol{h}) +]\boldsymbol{\epsilon}]^{-1} \quad \textbf{(1)}$$

Here,

$conv$ denotes convolution operator

g denotes the input to the system.

h denotes the system to be estimated

ϵ denotes added noise

τ denotes the shift in the convolution operation

The segmentation of blurred satellite images is challenging. While the pixel gradient based approaches render good results for image segmentation processes prior to detection, the blurry and noisy image background makes it very challenging to segment out the images. The radial gradient is expressed as [20]:

$$\boldsymbol{g} = \boldsymbol{Max}[\boldsymbol{E}(\frac{\partial}{\partial r} \oint_{x_i}^{x_f} \frac{I(x,y)}{\mu(i,j)} \boldsymbol{ds}|)] \quad \textbf{(2)}$$

To enhance the segmentation, radial gradient can be combined with entropy based segmentation wherein the entropy is computed as:

$$E = -P(I_{i,j})\log_2 I_{i,j} \qquad (3)$$

Max denotes the maximizing operation.

$\frac{\partial}{\partial r}$ denotes the radial gradient over the closed contour 'S'

ds denotes the differential area.

$\mu(i,j)$ denotes the mean pixel value.

Feature Extraction:

Satellite images contain vast amounts of data, often spanning multiple spectral bands. Analyzing this raw data directly can be computationally expensive and inefficient. Feature extraction reduces the complexity of the data by focusing on relevant characteristics while discarding redundant or irrelevant information. This process enables better decision-making and improves the performance of machine learning models and classification algorithms used for analyzing satellite imagery. By transforming high-dimensional data into relevant features, feature extraction simplifies analysis and enhances the accuracy of subsequent processes. Feature extraction in satellite images is a vital process for transforming raw data into actionable insights. By identifying and isolating relevant features, it enables efficient analysis and supports a wide range of applications, from agriculture to urban planning and disaster management. Despite challenges, advancements in AI, computational power, and data fusion promise to enhance the effectiveness and scalability of feature extraction methods, driving innovation in remote sensing and geospatial analysis [21].

Due to the potential overlap in pixel values among many categories of satellite images, it is essential to calculate characteristics that may distinguish these categories, as they possess distinct statistical qualities. It is essential to recognise that the features to be retrieved for various applications will differ based on individual case requirements. The statistical features calculated in this instance possess directional and area-specific factors. In this approach statistical features such as mean, standard deviation, hue, Saturation, Mean directional gradients, maximum gradient magnitude along x, Maximum gradients,, instantaneous gradients, solidity, centroid surface and sectored area have been computed.

Pattern Recognition

The pattern recognition is done through a deep neural network model which is optimized through the particle swarm optimization. The concept is presented next:

The Particle Swarm Optimization (PSO):

The PSO algorithm is an evolutionary computing technique, modeled after the social behavior of a flock of birds. In the context of PSO, a swarm refers to a number of potential solutions to the optimization problem, where each potential solution is referred to as a particle. The aim of the PSO is to find the particle position that results in the best evaluation of a given fitness function. In the initialization process of PSO, each particle is given initial parameters randomly and is 'flown' through the multi-dimensional search space. During each generation, each particle uses the information about its previous best individual position and global best position to maximize the probability of moving towards a better solution space that will result in a better fitness. When a fitness better than the individual best fitness is found, it will be used to replace the individual best fitness and update its candidate solution according to the following equations [22]:

$$\mathbf{v_{id}(t) = w \times v_{id}(t-1) + c_1 Ø_1(p_{id}\text{-}x_{id}(t\text{-}1)) + c_2 Ø_2(p_{gd}\text{-}x_{id}(t\text{-}1))} \qquad (4)$$

$$\mathbf{x_{id}(t) = x_{id}(t-1) + v_{id}(t)} \qquad (5)$$

Table. 1 List of variables used in PSO equations.

v	The particle velocity
x	The particle position
t	Time
c_1,c_2	Learning factors
Φ_1 ,Φ_2	Random numbers between 0 and 1
p_{id}	Particle's best position
p_{gd}	Global best position
w	Inertia weight

The PSO is used to adaptively update the weights of the neural network based on the minimization of the performance function.

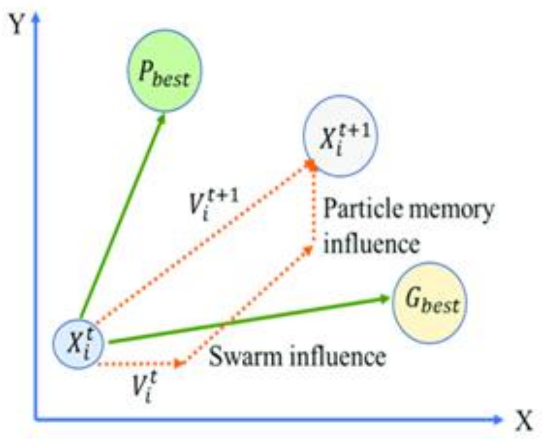

Fig.2 Visualization of PSO

While, traditional optimization focuses on a single objective function to be minimized or maximized. However, many real-world problems involve multiple conflicting objectives that cannot be optimized simultaneously without making trade-offs. Multi-objective optimization aims to find a set of solutions that represent the best trade-offs among these conflicting objectives, known as the Pareto front. PSO can be adapted to handle multi-objective optimization by incorporating mechanisms to guide the search towards discovering Pareto-optimal solutions efficiently. Several adaptations have been proposed to extend PSO for multi-objective optimization. One common approach is to modify the fitness evaluation mechanism to assess the quality of solutions based on their dominance relationship with respect to other solutions. This involves comparing solutions in terms of Pareto dominance, where one solution is considered better if it improves at least one objective without worsening any other. Additionally, strategies for maintaining diversity in the population are crucial to ensure thorough exploration of the Pareto front.

The ANN Model:

The ANN model is one of the most powerful regression models for pattern recognition. The mathematical model of the ANN is depicted in figure 3.

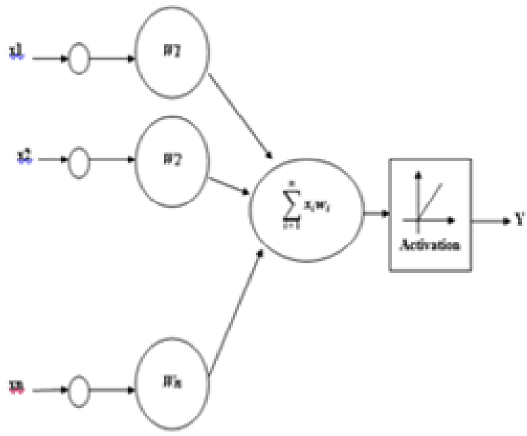

Fig.3 Mathematical Model of Neural Network

The output of the neural network is given by:

$$y = f\left(\sum_{i=1}^{n} \mathbf{XiWi} \ + \ \Theta\right) \qquad \textbf{(4)}$$

Where,

Xi represents the signals arriving through various paths,
Wi represents the weight corresponding to the various paths and
Θ is the bias.

In this approach, the back propagation based neural network model has been used with weight updating mechanism through the PSO [23]. The velocity factor of the PSO is incorporated to update the weights of the Neural Network Model:

$$\boldsymbol{w_{i+1} = w_i - \alpha\vartheta[H]^{-1}\frac{\partial e}{\partial w}} \qquad \textbf{(6)}$$

Here,

w represents the weights.
i represents the iterations.
α represents the learning rate.
$\boldsymbol{\vartheta}$ denotes the PSO velocity factor.
H represents the Hessian Matrix.
e represents the error of each iteration.

The training is stopped based on the mean square error or mse given by:

$$\boldsymbol{mse = \frac{\sum_{i=1}^{n} e_i^2}{n}} \qquad \textbf{(7)}$$

Performance Metrics

The performance of the approaches are accuracy since it's a classification problem that is being dealt with. The performance metrics are discussed:

$$\boldsymbol{Ac = \frac{TP+TN}{TP+TN+FP+FN}} \qquad \textbf{(8)}$$

Here,

Ac indicates accuracy
TP indicates true positive
TN indicates true negative
FP indicates false positive
FN indicates false negative

IV. RESULTS

The simulations are performed using the DOTA-v1.0 satellite image dataset, with 2806 images. The simulation platform is MATLAB.
The libraries used are:

1. Image Processing
2. Statistical
3. Neural Net
4. Deep Learning

The functions of these datasets have been used for the purpose of the analysis. The results are presented sequentially.

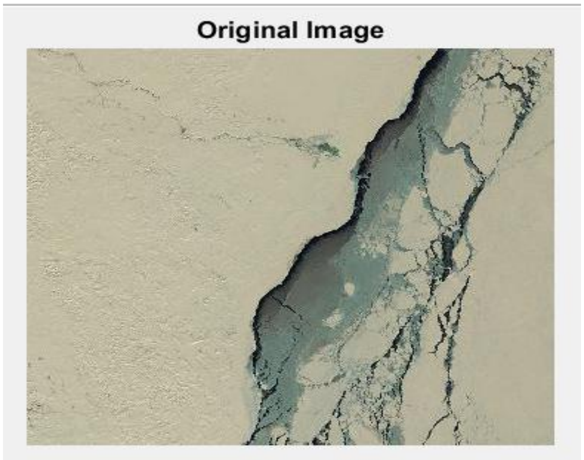

Fig.4 Original Image

Figure 4 depicts the original satellite image.

Fig.5 Noisy Blurred Image

Figure 5 depicts the noisy blurred image.

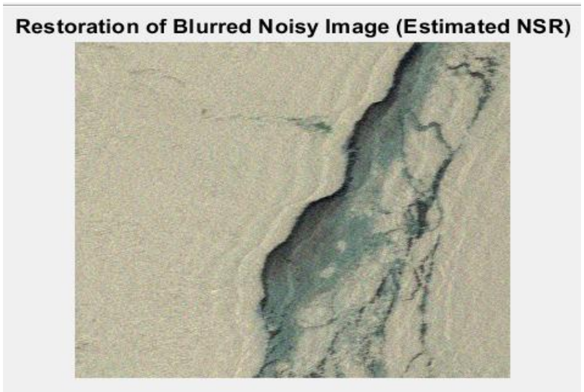

Fig.6 Deconvolution Based Restoration

Figure 6 depicts the deconvolution based image restoration.

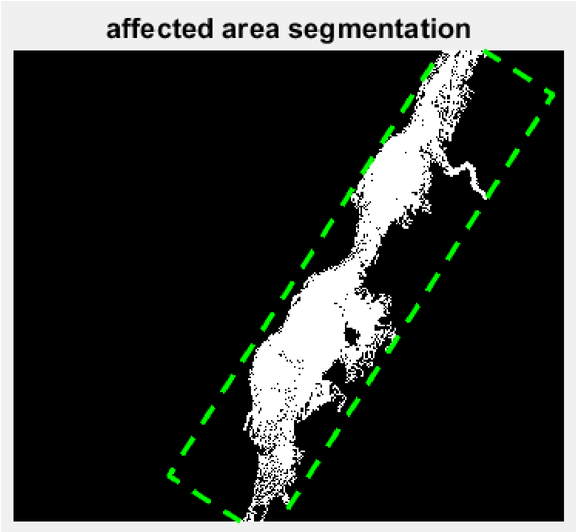

Fig.7 Segmentation

Figure 7 depicts the image after segmentation.

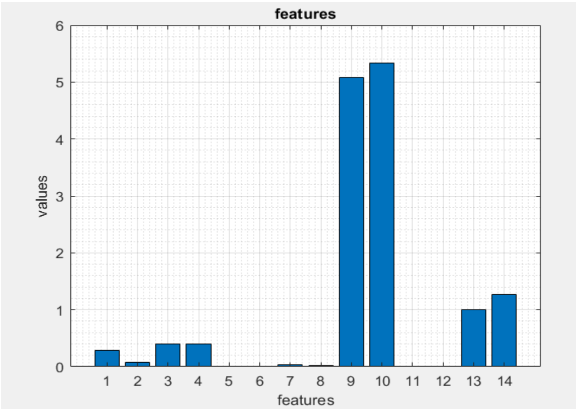

Fig.8 Bar plot of image features

Figure 8 depicts the bar plot of the image features.

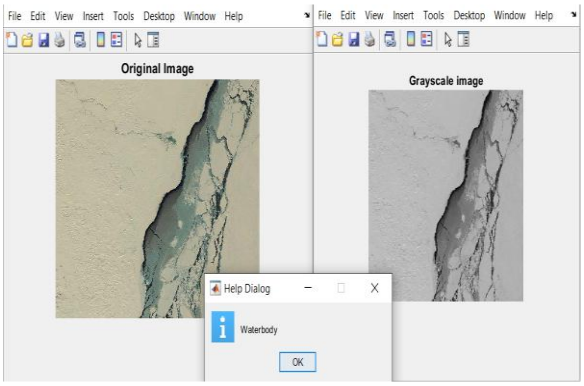

Fig.9 Object Detection

Figure 9 depicts the detection of the satellite object. In this case, it's the waterbody.

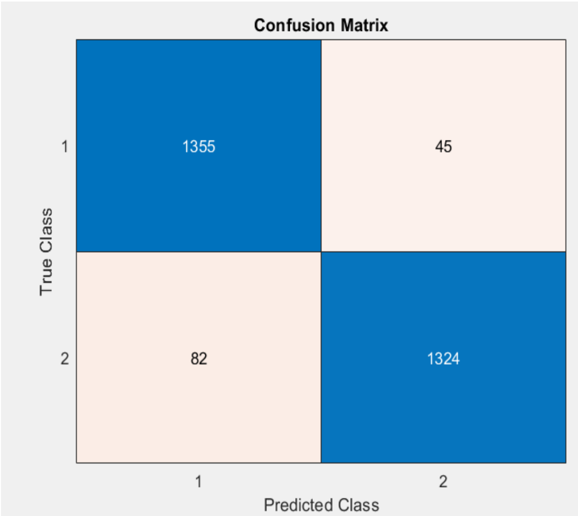

Fig.10 Model Confusion Matrix

Figure 10 depicts the model confusion matrix.

Based on the values of TP, TN, FP and FN, its is found that the proposed approach attains a classification accuracy of 95.5% for the image dataset. A comparison with existing work has been presented in table 2.

Table 2 Summary of Results

S.No.	Authors	Approach	Performance
1.	Miroszewski et al. [24]	Quantum-Kernel Support Vector Machines	Classification Accuracy of 91.9%
2.	Yang et al. [25]	RS-YOLOX	Classification Accuracy of 91.52%
3.	Proposed Approach		Classification Accuracy of 95.5%

It can be observed that the proposed approach attains a classification accuracy of 95.5% which is significantly higher compared to the existing work in the domain.

CONCLUSION

Satellite object detection has become a vital area of research in remote sensing, supporting applications like environmental monitoring, urban planning, and disaster management. With the growing volume of satellite imagery and the need for high precision, traditional object detection methods face challenges in scalability and accuracy. The proposed approach addresses the limitations of the existing approaches by combining image pre-processing, segmentation and classification through the PSO optimized deep neural network model. It has been found that the proposed approach attains a classification accuracy of 95.5% (approx.) which is significantly higher compared to existing work in the domain of research.

REFERENCES

1. M. Kisantal, S. Sharma, T. H. Park, D. Izzo, M. Märtens and S. D'Amico, "Satellite Pose Estimation Challenge: Dataset, Competition Design, and Results," in IEEE Transactions on Aerospace and Electronic Systems, 2020, vol. 56, no. 5, pp. 4083-4098.
2. B. Zhang et al., "Progress and Challenges in Intelligent Remote Sensing Satellite Systems," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 15, pp. 1814-1822.
3. L. He, J. Shan and D. Aliaga, "Generative Building Feature Estimation From Satellite Images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-13, 2023, Art no. 4700613.
4. M. Zhao, P. Olsen and R. Chandra, "Seeing Through Clouds in Satellite Images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-16, 2023, Art no. 4704616.
5. X. Zhu and C. Jiang, "Integrated Satellite-Terrestrial Networks Toward 6G: Architectures, Applications,

and Challenges," in IEEE Internet of Things Journal, 2021, vol. 9, no. 1, pp. 437-461.

6. D Yang, Y Zhou, W Huang, X Zhou, “5G mobile communication convergence protocol architecture and key technologies in satellite internet of things system”, - Alexandria Engineering Journal, Elsevier 2021, vol.60., no.1., pp. 465-476.
7. V. S. Chippalkatti, R. C. Biradar and S. S. Rana, "Recent Technology Trends in Satellite Communication Subsystems," 2021 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Bangalore, India, 2021, pp. 1-5.
8. H. Al-Hraishawi, H. Chougrani, S. Kisseleff, E. Lagunas and S. Chatzinotas, "A Survey on Nongeostationary Satellite Systems: The Communication Perspective," in IEEE Communications Surveys & Tutorials, vol. 25, no. 1, pp. 101-132, Firstquarter 2023.
9. O. Kodheli et al., "Satellite Communications in the New Space Era: A Survey and Future Challenges," in IEEE Communications Surveys & Tutorials, vol. 23, no. 1, pp. 70-109, Firstquarter 2021.
10. D. -H. Na, K. -H. Park, Y. -C. Ko and M. -S. Alouini, "Performance Analysis of Satellite Communication Systems With Randomly Located Ground Users," in IEEE Transactions on Wireless Communications, vol. 21, no. 1, pp. 621-634, Jan. 2022.
11. F. Davarian et al., "Improving Small Satellite Communications in Deep Space—A Review of the Existing Systems and Technologies With Recommendations for Improvement. Part I: Direct to Earth Links and SmallSat Telecommunications Equipment," in IEEE Aerospace and Electronic Systems Magazine, vol. 35, no. 7, pp. 8-25, 1 July 2020.
12. A Guidotti, S Cioni, G Colavolpe, M Conti, T Foggi, “Architectures, standardisation, and procedures for 5G Satellite Communications: A survey”, Computer Networks, Elsevier, 2020, vol.183, 107588.
13. K. -X. Li et al., "Downlink Transmit Design for Massive MIMO LEO Satellite Communications," in IEEE Transactions on Communications, vol. 70, no. 2, pp. 1014-1028, Feb. 2022.
14. N. Okati, T. Riihonen, D. Korpi, I. Angervuori and R. Wichman, "Downlink Coverage and Rate Analysis of Low Earth Orbit Satellite Constellations Using Stochastic Geometry," in IEEE Transactions on Communications, vol. 68, no. 8, pp. 5120-5134, Aug. 2020.
15. B. Al Homssi and A. Al-Hourani, "Optimal Beamwidth and Altitude for Maximal Uplink Coverage in Satellite Networks," in IEEE Wireless Communications Letters, vol. 11, no. 4, pp. 771-775, April 2022.
16. P. Wach and A. Salado, "Model-Based Requirements (TMBR) of a Satellite TTC Transponder," 2021 IEEE Aerospace Conference (50100), Big Sky, MT, USA, 2021, pp. 1-12.
17. P. Tang, P. Du, J. Xia, P. Zhang and W. Zhang, "Channel Attention-Based Temporal Convolutional Network for Satellite Image Time Series Classification," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 8016505.
18. X. Chen, C. Qiu, W. Guo, A. Yu, X. Tong and M. Schmitt, "Multiscale Feature Learning by Transformer for Building Extraction From Satellite Images," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 2503605.
19. M. Gazzea, M. Pacevicius, D. O. Dammann, A. Sapronova, T. M. Lunde and R. Arghandeh, "Automated Power Lines Vegetation Monitoring Using High-Resolution Satellite Imagery," in IEEE Transactions on Power Delivery, vol. 37, no. 1, pp. 308-316, Feb. 2022.
20. J Wang, M Bretz, MAA Dewan, MA Delavar -, “Machine learning in modelling land-use and land cover-change (LULCC): Current status, challenges and prospects”, Science of the Total Environment, Elsevier, 2022., vol.822, 153559.
21. JG Fernández, S Mehrkanoon, “Broad-UNet: Multi-scale feature learning for nowcasting tasks”, Neural Networks, Elsevier, 2021, vol.144, pp. 419-427.
22. T. Y. Tan, L. Zhang, C. P. Lim, B. Fielding, Y. Yu and E. Anderson, "Evolving Ensemble Models for Image Segmentation Using Enhanced Particle Swarm Optimization," in IEEE Access, 2019, vol. 7, pp. 34004-34019.
23. D Elhani, AC Megherbi, A Zitouni, F Dornaika, “Optimizing convolutional neural networks architecture using a modified particle swarm optimization for image classification”, Expert Systems with Applications, Elsevier 2023, vol.229, part A, 120411.

24. A. Miroszewski et al., "Detecting Clouds in Multispectral Satellite Images Using Quantum-Kernel Support Vector Machines," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2023, vol. 16, pp. 7601-7613.
25. L Yang, G Yuan, H Zhou, H Liu, J Chen, H Wu, “RS-Yolox: A high-precision detector for object detection in satellite remote sensing images”, Applied Sciences, MDPI, 2022, vol.12., , 8707.