Satellite Object Detection Using Machine Learning: A Review

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Abstract: **Satellite object detection using machine learning is a rapidly evolving field with applications in environmental monitoring, disaster management, urban planning, and national security. Satellites capture vast amounts of imagery daily, providing an enormous dataset that requires efficient and automated techniques for analysis. Machine learning, particularly deep learning, offers promising solutions for identifying and classifying objects such as buildings, vehicles, vegetation, and ships within satellite images. Machine learning models for satellite object detection typically involve several stages: preprocessing, feature extraction, model training, and validation. Preprocessing includes correcting image distortions, resizing, and enhancing image quality. This paper presents a review of machine learning based models for satellite object detection so as to render insights into developing future techniques which can yield high accuracy.**

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

I. INTRODUCTION

Satellite object detection has emerged as a critical technology in the modern era, enabling the extraction of meaningful information from satellite imagery for various applications [1]. The growing availability of high-resolution satellite data has made it possible to monitor and manage large-scale phenomena on Earth, ranging from urbanization and environmental changes to disaster response and security concerns. The applications of satellite object detection are diverse and impactful [2].

In environmental monitoring, machine learning models detect deforestation, track wildlife habitats, and monitor water resources. For disaster management, these systems help identify damaged infrastructure, locate survivors, and assess the extent of natural disasters such as floods and wildfires [3]. Urban planners use satellite imagery to analyze population growth, plan transportation networks, and monitor illegal construction. Additionally, military and security agencies leverage these technologies for border surveillance, identifying unauthorized activities, and tracking naval vessels. The block diagram of satellite communications is presented [4].

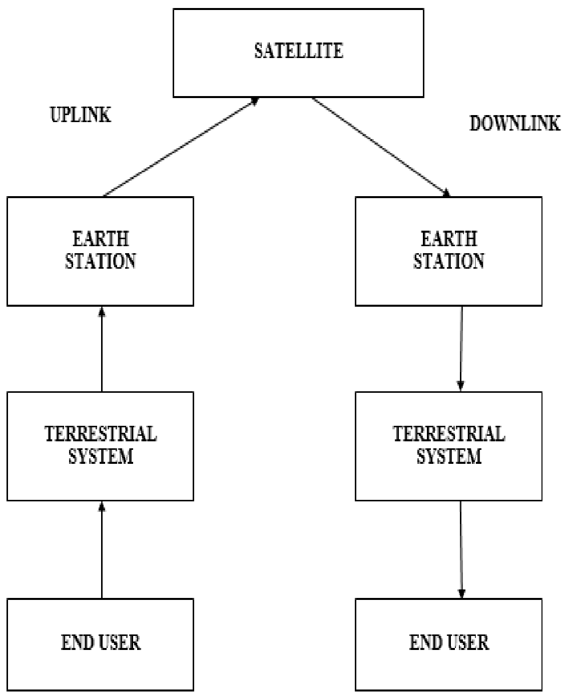

Fig.1 Illustration of typical image forgery

Figure above depicts the block diagram of satellite communications which has the following major blacks [5]:

1. Earth Station.
2. Terrestrial System
3. Satellite
4. End User.

Despite its potential, satellite object detection using machine learning faces several challenges. One significant hurdle is the variability in satellite imagery caused by differences in resolution, lighting conditions, and atmospheric disturbances [6]. Annotating large datasets for model training is labor-intensive and time-consuming. Moreover, detecting small objects, such as vehicles or fishing boats, in high-resolution images can be difficult due to their scale and similarity to background elements. Additionally, computational resources required for training and deploying these models are often costly and inaccessible for many organizations [7].

II. APPLICATIONS OF SATELLITE OBJECT DETECTION

Environmental Monitoring: One of the most pressing needs for satellite object detection lies in environmental monitoring [8]. With climate change accelerating environmental degradation, it is essential to track changes in land cover, deforestation, melting glaciers, and rising sea levels. Satellite object detection enables the identification of specific features, such as forest cover, water bodies, and agricultural fields, which helps in assessing the health of ecosystems. For instance, detecting illegal logging activities in rainforests or monitoring desertification trends allows policymakers to take timely and informed action [9].

Disaster Management: Natural disasters, such as earthquakes, floods, hurricanes, and wildfires, pose significant threats to human life and infrastructure. Satellite object detection is a vital tool for disaster management, as it provides real-time information on the extent of damage and helps identify affected areas [10]. For example, during floods, satellite imagery can be used to detect submerged roads and buildings, guiding rescue operations and resource allocation. Early detection of events, such as forest fires, also enables authorities to take preventive measures and minimize losses [11].

Urban Planning and Infrastructure Development: As urbanization accelerates globally, there is a growing need for effective urban planning and infrastructure development [12]. Satellite object detection aids in mapping urban growth, identifying illegal construction, and analyzing land use patterns. By detecting objects such as roads, buildings, and vehicles, urban planners can design better transportation networks and optimize land usage. This technology also supports the monitoring of infrastructure projects, ensuring they are completed on time and within the designated parameters [12].

Security and Defense: National security and defense are other critical areas where satellite object detection plays a pivotal role. Border surveillance, detection of unauthorized activities, and tracking military assets are essential for ensuring security [14]. For example, identifying suspicious vessels in maritime zones or monitoring troop movements in conflict areas can provide strategic insights to defense agencies. This capability is especially important in regions where traditional ground-based surveillance systems are difficult to deploy [15].

Agricultural Management: In the agricultural sector, satellite object detection addresses the need for precision farming and resource optimization. By identifying crop types, assessing crop health, and monitoring irrigation systems, this technology helps farmers maximize yields and reduce waste. Detecting pest infestations and drought-affected areas enables timely interventions, minimizing economic losses and ensuring food security [16].

Global Challenges and Sustainability: Satellite object detection is crucial in addressing global challenges such as climate change, food security, and sustainable development. For example, monitoring greenhouse gas emissions from industrial facilities or tracking urban sprawl can support international efforts to reduce carbon footprints. The ability to detect and analyze changes in the Earth's surface over time provides valuable data for achieving the United Nations' Sustainable Development Goals (SDGs) [17].

III. MACHINE LEARNING FOR SATELLITE OBJECT DETECTION

Artificial Intelligence and Machine learning have become an increasingly sought after domain in this recent time. The integration of machine learning in satellite object detection is revolutionizing the way we analyze and interpret satellite imagery. With the ever-increasing volume of high-resolution satellite data, traditional manual or rule-based approaches are no longer sufficient to process and analyze such vast datasets. Machine learning provides automated, efficient, and accurate techniques for identifying and classifying objects in satellite images. This essay explores the need for machine learning in satellite object detection, emphasizing its advantages and applications across various domains [18].

Fig.2 A typical Satellite Image

Figure above depicts a typical satellite image. The need for machine learning arises from its ability to enable advanced applications in satellite imagery analysis. For example, in environmental monitoring, machine learning models can detect deforestation, track glacier movements, and monitor wildlife habitats. In urban planning, these models help identify illegal construction, analyze traffic patterns, and map urban sprawl. Similarly, in disaster management, machine learning facilitates the rapid identification of damaged infrastructure and affected areas, enabling timely response and resource allocation. The common machine learning models which have been used for satellite object detection are [19]:

Support Vector Machine (SVM): Before the advent of deep learning, traditional machine learning models such as Support Vector Machines (SVM), Decision Trees, Random Forests, and K-Nearest Neighbors (KNN) were widely used for satellite object detection. These models typically relied on handcrafted features, such as texture, edges, and spectral indices, to distinguish between different objects.

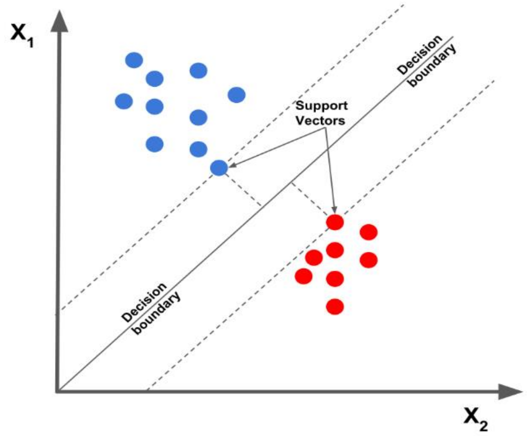

Fig.3 The SVM Model

Figure 3 depicts the SVM Model.

The SVM classifies based on the hyperplane.
The selection of the hyperplane H is done on the basis of the maximum value or separation in the Euclidean distance d given by:

$$\boldsymbol{d} = \sqrt{x_1^2 + \cdots \ldots \ldots . x_n^2} \qquad \textbf{(1)}$$

Here,
x represents the separation of a sample space variables or features of the data vector,
n is the total number of such variables
d is the Euclidean distance

The (n-1) dimensional hyperplane classifies the data into categories based on the maximum separation. For a classification into one of **'m'** categories, the hyperplane lies at the maximum separation of the data vector **'X'.** The categorization of a new sample **'z'** is done based on the inequality:

$$\boldsymbol{d_x^z = Min(d_{C1}^z, d_{C2}^z \ldots d_{C2=m}^z)} \quad \textbf{(2)}$$

Here,
d_x^z is the minimum separation of a new data sample from **'m'** separate categories
$d_{C1}^z, d_{C2}^z \ldots d_{C2=m}^z$ are the Euclidean distances of the new data sample **'z'** from m separate data categories.

For instance, SVMs are effective for binary classification tasks, such as distinguishing between urban and rural areas, while Random Forests are used for multi-class classification problems, such as land cover mapping. However, these models struggle with complex patterns in high-resolution imagery and require extensive feature engineering, which limits their scalability and accuracy

Neural Networks:

Owing to the need of non-linearity in the separation of data classes, one of the most powerful classifiers which have become popular is the artificial neural network (ANN). The neural networks are capable to implement non-linear classification along with steep learning rates. The neural network tries to emulate the human brain's functioning based on the fact that it can process parallel data streams and can learn and adapt as the data changes. This is done through the updates in the weights and activation functions.

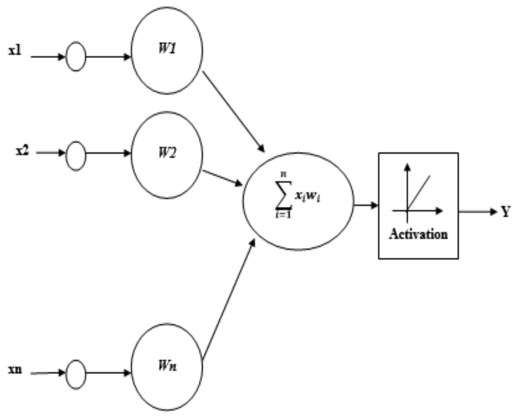

Fig.4 The ANN Model

The input-output relation of a CNN is given by:

$$\boldsymbol{y = f(\textstyle\sum_{i=1}^{n} x_i w_i + b)} \quad \textbf{(3)}$$

Here,
x denote the parallel inputs
y represents the output
w represents the bias
f represents the activation function

The neural network is a connection of such artificial neurons which are connected or stacked with each other as layers. The neural networks can be used for both regression and classification problems based on the type of data that is fed to them. Typically the neural networks have 3 major conceptual layers which are the input layer, hidden layer and output layer. The parallel inputs are fed to the input layer whose output is fed to the hidden layer. The hidden layer is responsible for analysing the data, and the output of the hidden layer goes to the output layer. The number of hidden layers depends on the nature of the dataset and problem under consideration. If the neural network has multiple hidden layers, then such a neural network is termed as a deep neural network. The training algorithm for such a deep neural network is often termed as deep learning which is a subset of machine learning. Typically, the multiple hidden layers are responsible for computation of different levels of features of the data.

Convolutional Neural Networks (CNNs): The family of CNNs are the backbone of modern satellite object detection. CNNs automatically learn hierarchical features from raw images, eliminating the need for manual feature extraction. The Convolutional Neural Networks (CNNs) can automatically extract hierarchical characteristics from images, they have become the mainstay for image classification applications. These neural networks perform exceptionally well in applications like picture identification because they are specifically made for processing organised grid data [20].

Convolutional, pooling, and fully linked layers are among the layers that make up a CNN's architecture. Convolutional layers identify patterns in the input image by applying filters, hence identifying local features. By reducing spatial dimensions, pooling layers preserve significant information. High-level features are integrated for categorization in fully connected layers.

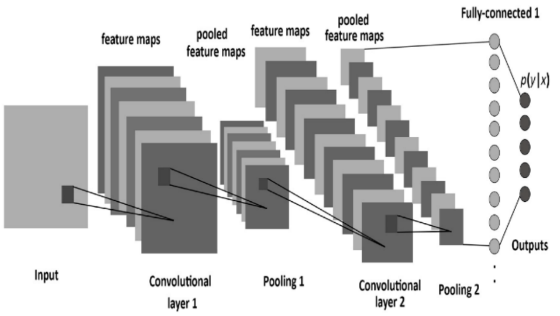

Fig.5 The CNN Model

The convolution operation is given by:

$$\boldsymbol{x(t) * h(t) = \int_{-\infty}^{\infty} x(\tau)h(t-\tau)d\tau} \qquad \textbf{(4)}$$

Here,
x(t) is the input
h(t) is the system under consideration.
y is the output
*is the convolution operation in continuous domain
For a discrete or digital counterpart of the data sequence, the convolution is computed using:

$$\boldsymbol{y(n) = \sum_{-\infty}^{\infty} x(k)h(n-k)} \qquad \textbf{(5)}$$

Here
x(n) is the input
h(n) is the system under consideration.
y is the output
*is the convolution operation in discrete domain

The CNN has the following layers.

Convolutional Layers: In feature extraction, convolutional layers are essential. In order to identify patterns like edges, textures, and forms, filters, also known as kernels, convolve across the input image. Through weight sharing and parameter sharing, convolutional processes enable the network to learn complicated representations by capturing spatial hierarchies.

Pooling Layers: In order to down sample feature maps, pooling layers come after convolutional layers. Max pooling and average pooling are two popular pooling techniques that minimise spatial dimensions without sacrificing significant information. This procedure improves translation invariance and aids in the management of computational complexity.

Fully Connected Layers: Fully connected layers combine high-level features for classification and come after convolutional and pooling layers. A dense network is created when all of the neurons in one layer connect to all of the neurons in the layer above. The last completely connected layer generates probability outputs for the final classification through the use of an activation function logic.

Final Classification: By introducing non-linearity, activation functions allow the network to discover intricate correlations within the data. Rectified Linear Unit, or ReLU, is a popular CNN activation function that creates non-linearity by outputting the input for positive values and zero for negative values.
CNN training entails gradient descent and backpropagation to optimise weights and biases. The discrepancy between expected and actual values is measured using loss functions. Well-known optimisation techniques, such as Adam and RMSprop, modify weights in order to reduce loss. To avoid overfitting, data augmentation and dropout are frequently employed.

Popular CNN-based architectures include:

AlexNet and VGG: Early CNN models like AlexNet and VGG laid the foundation for deep learning in computer vision. While effective for simple classification tasks, their high computational requirements make them less suitable for large-scale satellite imagery.

ResNet (Residual Networks): ResNet introduced skip connections, addressing the vanishing gradient problem and allowing for deeper networks. It is widely used for feature extraction in satellite imagery and transfer learning tasks.

Inception Networks: Inception models, such as GoogleNet, utilize multi-scale convolutional filters, making them effective for detecting objects of varying sizes in satellite images.

RCNN: The R-CNN family of models revolutionized object detection by combining region proposal methods with CNNs. Key models in this category include:

R-CNN and Fast R-CNN: These models generate region proposals, classify them, and refine their bounding boxes. However, their slow processing speed limits their applicability to real-time scenarios. Faster R-CNN: By introducing a Region Proposal Network (RPN), Faster R-CNN significantly improved the speed and accuracy of object detection. It is commonly used for detecting buildings, vehicles, and other objects in satellite imagery.

Single-shot detectors (SSD) and You Only Look Once (YOLO): These models are designed for real-time object detection, making them highly efficient for satellite applications.
SSD: SSD predicts object classes and bounding boxes directly from feature maps, enabling faster detection. It is particularly useful for identifying objects in densely populated areas, such as urban environments.

YOLO: YOLO divides the image into a grid and predicts bounding boxes and class probabilities for each cell in a single pass. Its real-time performance makes it suitable for tasks like monitoring moving objects, such as ships or vehicles.

Semantic and Instance Segmentation Models
In addition to object detection, satellite imagery often requires semantic or instance segmentation to delineate object boundaries. Models like U-Net and Mask R-CNN excel in these tasks:

U-Net: U-Net is widely used for semantic segmentation tasks, such as delineating land cover types or water bodies. Its encoder-decoder architecture is particularly effective for extracting fine details.

Mask R-CNN: An extension of Faster R-CNN, Mask R-CNN adds a segmentation branch, enabling instance-level segmentation. It is commonly used for tasks such as counting individual trees or identifying buildings in satellite imagery.

IV. PREVIOUS WORK

The previous work section presents the contemporary work in the domain.

Haryono et al. [21] proposed a two-stage process of delineating a horizontal bounding box and then converting it into an oriented bounding box is inefficient. To improve detection, a box-boundary-aware vector can be estimated based on a convolutional neural network. Specifically, authors propose a ResNeXt101 encoder to overcome the weaknesses of the conventional ResNet, which is less effective as the network depth and complexity increase. Owing to the cardinality of using a homogeneous design and multibranch architecture with few hyperparameters, ResNeXt captures better information than ResNet. Experimental results demonstrate more accurate and faster oriented object detection of our proposal compared with a baseline, achieving a mean average precision of 89.41%..

Lilay et al. [22] proposed that in Previous studies found issues with the satellite images coarser spatial resolution, the use of standard statistical methods as classifiers, and the difficulty in optimal patch size selection when patch-based classification is used. To address these issues, authors suggested a deep learning-based semantic segmentation model that could be utilized as a pixel-level land cover classification technique. The suggested technique employed high-resolution Sentinel-2 satellite images of our study area (GNP) as a dataset and constructed and assessed pixel-level classification models. As a deep learning-based classification model, authors have used the Link-Net architecture and its encoder part was modified further to incorporate the state-of-the-art architecture called ResNet34. The developed models, support vector machine with CNN features (CNN–SVM), random forest with CNN features (CNN-RF), LinkNet model with ResNet-34 as encoder (LinkNet-ResNet34) attain average F1-Score values of 81%,82%, and 87.4% respectively.

Li et al. [23] reviewed the tasks of object detection, object tracking, and object segmentation based on satellite videos, providing a comprehensive overview of progress in related datasets and algorithm research. Finally, we establish the first public benchmark of multitask algorithms for satellite video object detection, object tracking, and object segmentation, evaluating and analyzing the performance of a total of 47 representative algorithms under different tasks on the constructed dataset.

Pang et al. [24] proposed a fast and lightweight intelligent satellite on-orbit computing network (SOCNet). First, the overall network architecture based on the idea of flat multibranch feature extraction is proposed to accelerate model inference and reduce the network depth. Second, we propose the idea of exchanging a larger receptive field for network depth and combine the idea of depthwise separable convolution to further reduce the amount of parameters. Authors design a feature extraction method of coupled fine–coarse-grained for efficient feature extraction. Finally, global average pooling is used for feature fusion to further reduce the network parameters' amount and computational complexity.

Yan et al. [25] proposed an intelligent and high-precision method for extracting tailings pond information from high-resolution images, which improves deep learning target detection model: faster region-based convolutional neural network (Faster R-CNN). A comparison study is conducted and the model input size with the highest precision is selected. The feature pyramid network (FPN) is adopted to obtain multiscale feature maps with rich context information, the attention mechanism is used to improve the FPN, and the contribution degrees of feature channels are recalibrated. The model test results based on GoogleEarth high-resolution remote sensing images indicate a significant increase in the average precision (AP) and recall of tailings pond detection from that of Faster R-CNN by 5.6% and 10.9%, reaching 85.7% and 62.9%, respectively.

Existing Challenges:

The comparative analysis renders insight into the basic methodologies used. The salient features have also been discussed. While these models offer remarkable capabilities, they also face challenges [26]. High computational requirements, dependency on large labeled datasets, and difficulty in detecting small objects in cluttered backgrounds are common limitations. Additionally, the variability in satellite imagery, caused by changes in resolution, lighting, and atmospheric conditions, necessitates robust model designs and domain-specific training [27].

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:

$$\boldsymbol{Ac} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}} \qquad \textbf{(6)}$$

Here,
Se indicates sensitivity
Ac indicates accuracy
TP indicates true positive
TN indicates true negative
FP indicates false positive
FN indicates false negative

CONCLUSION

Machine learning has revolutionized satellite object detection, offering faster, more accurate, and scalable solutions for analyzing satellite imagery. The need for satellite object detection arises from its ability to address a wide range of challenges in environmental conservation, disaster management, urban planning, security, and agriculture. By leveraging advanced technologies such as machine learning and artificial intelligence, satellite object detection offers accurate, scalable, and cost-effective solutions for monitoring and managing the Earth's resources. While challenges remain, ongoing research and innovation continue to address these limitations, unlocking new possibilities for applications across various domains. As the technology matures, it holds the potential to transform how we monitor and manage the Earth's resources and respond to global challenges. This paper presents a comprehensive review on satellite object detection and the various state of the art machine learning and deep learning models for the purpose.

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