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A REVIEW OF REMOTE SENSING SATELLITE IMAGE PROCESSING TECHNIQUES.

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This paper offers a detailed review of the cutting-edge technology involved in digital image processing it pertains to the use of satellite-based sensors to acquire remote sensed pictures. It is possible to classify remote sensing image processing methods into four broad categories: image pre-processing, enhancement, transformation, and classification. Image pre-processing is the stage whereby distortions in the form of radiometric distortions, atmospheric distortions, and geometric distortions in the original image are eliminated. The data is preprocessed, and then enhancement methods are employed so that the picture can be shown clearly and read by the human eye. It consists of methods such as differentiating surface aspects and visual interpretation. Effective thematic maps of specific land use and land cover may be created by a combination of transformation, which seeks to identify specific features of Earth's surface, and classification, which groups the pixels.
Keywords: Digital image processing, Satellite-based sensors, enhancement, transformation, and classification.

I. INTRODUCTION

The military, geographic surveys, surveillance, and environmental monitoring are just some of the many real-time applications that use satellite image categorization [1]. The need for accurate categorization, which can only achieve via the efficient classification of satellite photos [2]. The use of machine learning to help extract useful information from satellite photos is a growing trend. More training data is needed when working with high-resolution satellite photos. So, semi-supervised adversarial techniques are an increasing subfield to ML-based algorithms [3] for extracting information from satellite pictures. When processing inputs and producing trustworthy classification, semi-supervised conflicting approaches use a hybrid of unsupervised training and labeled data [4].Two distinct phases, picture restoration and enhancement, make up the preprocessing technique. The salt and pepper noise, Gaussian noise, and speckle noise[5] in satellite pictures are removed using a 2D Bilateral Frequency Domain Wavelet Filter (2D-BFDWF) for image restoration. Image enhancement is the second step in the preprocessing of images. This improved picture results from the 2D edge Preservation Gradient Histogram Improvement (2D EPGHI) technique. The use of a semi-supervised adversarial learning approach for extracting information from satellite photos [6]; Architectural expansion and improvements [7]. Four distinct input-feeding methods use to validate the suggested approach, each improving the quality of the processed data by creating a more significant correlation [8]. The semi-supervised adversarial learning approach is to rely on a pair of learning-based networks [9]. To start, a segmentation network using unlabeled input and supervised learning to parse. Following this is a discriminator block, a well-trained version of the commonplace 2D Iterative CNN used to enhance segmentation precision. All studies conducted used both labelled and unlabeled samples.

The following paper is organized as Section II, examines the basic processing steps of satellite image processing techniques. Section III explains a literature survey on image analysis, including advanced preprocessing, enhancement, transformation, and classification techniques. Section IV provides a summary of Remote Sensing Applications. Section V concludes.

II. Basic Processing Steps of Satellite Image Processing

Satellite Image Analysis

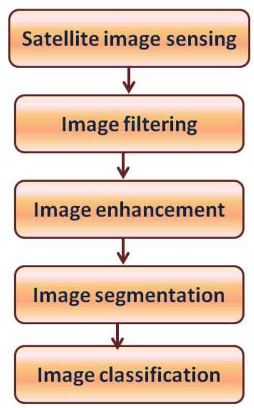

Fig 1(a). Flow diagram of Satellite image processing

The flow diagram of Satellite image processing is shown in Figure 1(a). Image sensing, filtering, enhancement, segmentation and classification are the primary processing phases in remote sensing.

Image sensing:

An image is a pictorial depiction of anything that includes a large amount of data. In digital image processing, one of the most important things to do is to analyze the picture and get information from it in a way that doesn't affect other parts of the picture. This is done so that certain tasks can be done.

Image filtering:

Even though quantitative improvements for lighting, climate conditions, and sensor characteristics perform before data presentation to the recipient, the image may still need to optimize for the captured images. Following image sensing, multiple filters are used to eliminate noise from the image.

Image enhancement:

Enhancements are used to make images simpler to comprehend visually. The benefit of digital imaging is that change the digital pixel values in a picture. Image enhancement techniques are classified into four categoriesis shown in Figure 1(b).

(a) *Radiometric Enhancement*: Radiometric enhancements are methods that change the colors of certain ranges of pixel values on the screen to improve the contrast between different parts of the earth's surface.

(b) *Spatial Enhancement* : A remote sensing system's spatial resolution define as the number of line pairs per millimeter, commonly used when working with analogue pixels, which is the essential component of digital imaging. Spatial frequency adjusts pixel values based on the importance of neighboring pixels.

(c) *Spectral Enhancement* : The practice of producing new spectral data from existing bands is known as spectral augmentation.

(d) *Geometric Enhancement:* Geometrical detail in a picture is altered for improved perception and processing. The surrounding pixel defines geometric enhancement. The new pixel value generated from the brightness pixels of a collection of surrounding pixels causes differences in the geometric detail perceived. Smoothing, edge detection and enhancement, and line detection and enhancement are all examples of geometric enhancement in remote sensing. Image sharpening is the result of edge and line improvements.

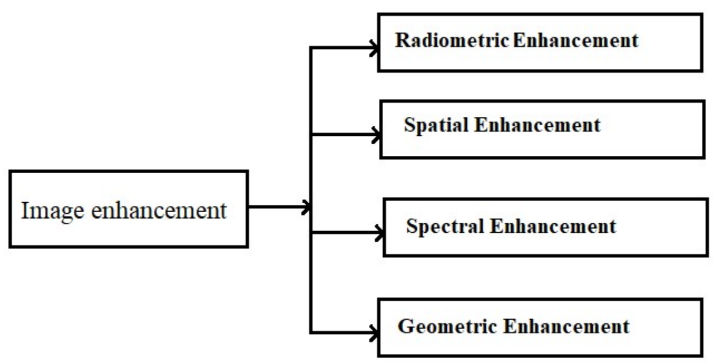

Fig 1 (b). Classification of Image Enhancement

Image segmentation:

Image segmentation is a technique used in digital picture processing to split an image into several sections, frequently based on the properties of the pixels in the image. Most of this relies on two fundamental features of intensity values, i.e., similarity and non-similarity. The first method is an image based on a sharp change in intensity, i.e., image edges. The second strategy is pre-defined criteria for partitioning pictures.

Image Classification:

The technique of classifying all pixels in a picture generated through remotely sensed satellite data in order to get a certain set of labels or land cover themes is known as image classification. In other circumstances, the examination may focus on the category itself.

III. LITERATURE SURVEY

Image processing techniques:

S. Ji et al. [10] described that deep learning-based models are only helpful when trained using many annotated source photographs similar to the target images in remote sensing image segmentation and classification. This study uses fresh target remote sensing photographs to adjust the domain for land cover categorization.GANs align source and target images in image, feature, and output spaces using two-stage adversarial learning. To categorize the land cover types in the target photos, a fully convolutional network (FCN) is trained using the source images as a translation into the target's style. A comprehensive framework creates combining domain adaptation with segmentation.

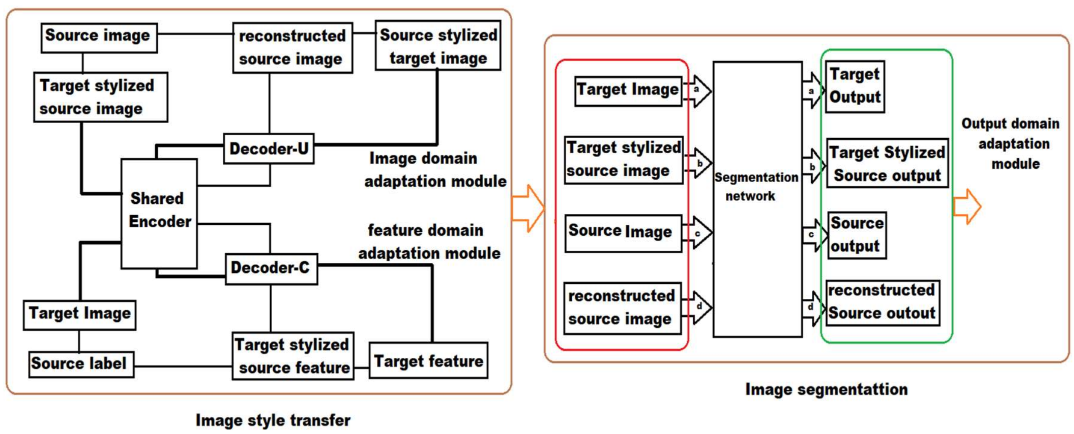

Fig. 2. FSDAN architecture

S.Scepanovic et al. [11] explained that to keep on the ecosystem and learn how humans are altering it, land cover (LC) mapping is crucial. Deep learning models use for low-scale LC mapping tasks. The many state-of-the-art models in natural photos used for a given remote sensing application and the dataset remain to be determined. This piece used satellite imaging radar data to solve this topic in the context of cartographically in place of the core LC classes. To get an accurate picture of Finland's land cover, C-band SAR photos captured by the ESA's Sentinel-1 satellite during the summer of 2018. The trained models are differentiated between the five main classes based on CORINE, using the CORINE LC map as a reference. Seven of the most advanced models for semantic segmentation are U-Net, DeepLabV3+, PSPNet, BiSeNet, SegNet, FC-DenseNet, and FRRN-B. FS DAN and BiSeNet architecture are shown in Figures 2 and 3. U-Net and DeepLabV3+ illustrate in Figure 4 and Figure 5. Compared to the models, they performed admirably, with an average accuracy of 87.1 and 93.1 % and suitable to the excellent agreement (Kappa statistic between 0.75 and 0.86). Fully convolutional DenseNets (FC-DenseNet) and SegNet (encoder-decoder-skip), the two top models are shown in Figure 6 and Figure 7. SegNet had a much lower inference time.

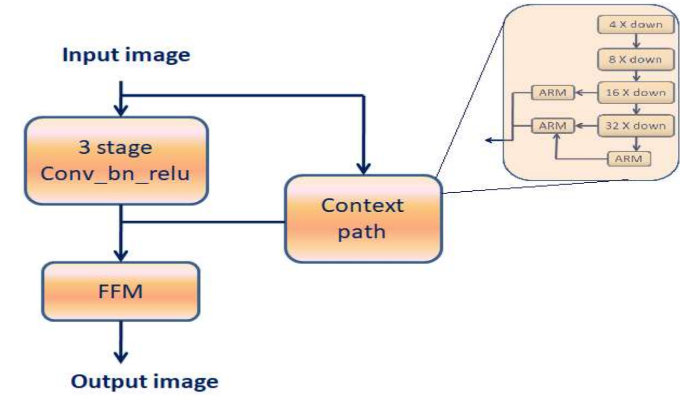

Fig 3. Bilateral Segmentation Network

Z. Zheng et al. [12] give details of significant advancements in the use of deep convolutional neural networks (DCNNs) for the semantic segmentation of high-resolution (HR) remote sensing pictures. But DCNNs' loss of spatial information when reduced feature map resolution causes objects' boundaries to blur and causes tiny things to misclassify. Further hindering performance is that HR photos include various geographical features and a class imbalance. A fully-contained deep convolutional neural network (DCNN) network called GAM Net reconciles the tension between broad, overarching concepts and fine-grained specifics. Multi-scale feature extraction and boundary recovery achieve in a single pass thanks to a specialized attention and gate module (GAM). The integration module uses in a skip-connected encoder-decoder network. In the meantime, an auxiliary loss is added to a composite loss function to make it easier to keep an eye on GAM and improve the performance of the integration module.

H.jung et al. [13] described that convolutional neural networks (CNNs) for image processing in remote sensing had advanced quickly. As a result of its widespread use in fields like catastrophe assessment and city planning, approaches for reliably recovering building footprints from distant sensed photos have garnered significant attention. Semantic segmentation with U-Net-like CNN architecture makes it simple to extract building footprints. However, owing to several obstacles around target objects, accurately collecting the borders of segmentation masks remains a significant challenge. This research presents an approach for improving the bounds of segmentation masks by fine-tuning the edges of structures identified in remotely sensed photos.

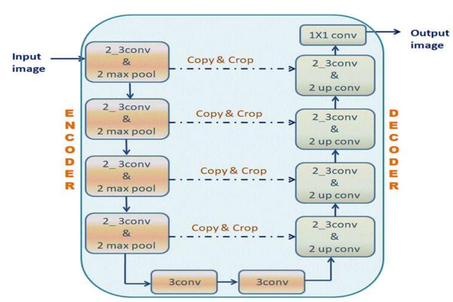

Figure 4. U-NET

The suggested technique uses holistically nested edge detection (HED) to extract edge features from an encoder of a predetermined design. As part of the proposed boundary enhancement (BE) module, merge an extracted edge with a segmentation mask, using both strengths.A novel methodology using a HED unit and BE module, which is transferable to other semantic segmentation networks with encoder-decoder architectures, to allow the proposed method to adapt efficiently to a broad range of situations. Deep Globe, Urban3D, WHU [high-resolution (HR)], low-resolution (LR), and Massachusetts uses for the experiments. The results show that our suggested strategies outperform the conventional means of collecting footprints of buildings. The proposed system's efficacy studies compared it to other backbone designs, including U-Net, ResUNet++, TernausNet, and U-shape spatial pyramid pooling (USPP). Using quantitative and qualitative research concluded that the suggested strategy was better than the ones that came before it for all datasets and backbone networks.

O. Tasar et al. [14] illustrate that researchers have started paying more attention to domain adaptation to get beyond the limited generalisation capabilities of machine learning models when segmenting large-scale satellite pictures. The majority of current methods aim to generalise the model to new settings. However, the availability of various sources and target domains with varying data distributions means that such a setup limits the approaches' scalability. Aside from that, the ever-increasing volume of satellite photos needs flexible classifiers to keep up. DAugNet proposes satellite pictures' unsupervised, multisource, multi-target, and permanent domain adaptation. A classifier and an information amplifier are the two main components. Even when more and more data provides over time, the data augmenter, an external network, may execute an unsupervised style transfer across several satellite photos. By showing the classifier a lot of different kinds of data during each training round, it can better handle differences in how data spreads across domains.

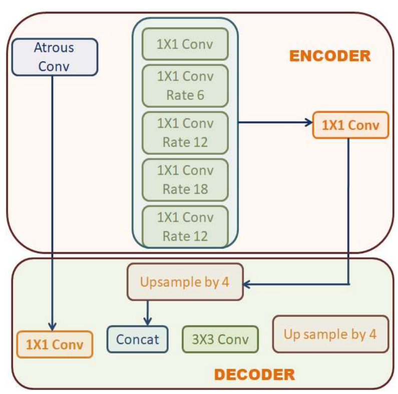

Figure 5. DeepLabV3

J. H. Giraldo et al. [15] points up that Computer vision relies heavily on Moving Object Segmentation (MOS). MOS becomes very difficult for both still and moving camera sequences due to unwanted fluctuations in the backdrop scene. Many deep learning approaches for MOS and their results have been promising. However, when exposed to previously unseen movies, the performance of these approaches remains the same, and vast quantities of data are often necessary for deep learning models to prevent overfitting. Many computer vision applications

are looking to graph learning for help since it offers methods for capitalizing on the geometrical makeup of data. These results bring MOS to the ideas of graph signal processing. First, a novel approach of segmentation, background initialization, graph creation, unseen sampling, and a semi-supervised learning technique inspired by the recovery of graph signals. Second, new theoretical advancements are presented, including limits for the condition number of the Sobolev norm and the sample complexity of semi-supervised learning. Compared to deep learning approaches, our system achieves comparable results on static and moving camera movies while using less labelled data. Our technique modify for use in Video Object Segmentation (VOS) tasks and tested on six open-source datasets, where it shows to beat several other state-
of-the-art approaches.

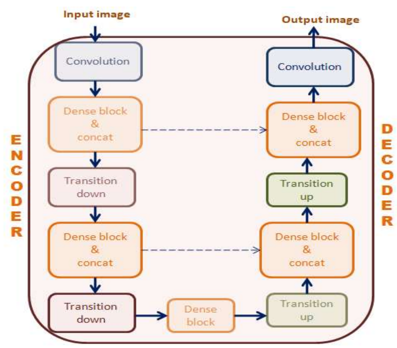

Figure 6. FC-Dense Net

Y. Huang et al. [16] exemplify that detecting objects in motion is an active and challenging research area. The trick lies in identifying and setting the modified section apart from the rest of the document. Moving-object recognition also often relies on the relationship between the multi-dimensional information of input frames. A new and efficient technique for detecting moving objects in videos introduce here. This approach is novel because it simultaneously considers the time and space domains when calculating the relationship between multi-dimensional information. As it is, most algorithms for detecting moving objects do not combine temporal and spatial dimensions. Some detection issues may arise if, for example, the background information of stationary or slowly moving items updates too often, leading to an insufficiently recognized foreground area. To address these drawbacks, apply the enhanced ICA approach to the first time-domain segment of the continuous multi-frame pictures and then spatially integrate the resulting signals. In cases where only minor changes have occurred, it could identify and isolate the unique input signals necessary to correctly identify and extract the foreground target. VTD-FastICA is the name of the suggested algorithm. Extensive testing has demonstrated that it outperforms the state-of-the-art algorithms for recognizing moving objects, particularly in challenging conditions involving occlusion and lengthy periods when only subtle changes occur. Analyze our method's performance under varying conditions, showing that the suggested algorithm is applicable in the current world.

S. D. Roy et al. [17] show that detecting moving things in the wild is a well-studied field. However, there has yet to be much research done on moving object recognition in extreme weather since there isn't a good benchmark dataset for such settings. To fill this gap,"Extended

Tripura University Video Collection (E-TUVD)", a diversified dataset of complicated atmospheric conditions used as a baseline for future video datasets. E-TUVD is the most significant video dataset for identifying moving objects in poor weather and atmospheric conditions. The collection includes 147 videos ranging in length from 1 to 5 minutes. This research focuses on creating ground-truth photos of interesting moving things on E-TUVD to assess any object detection model—the best-performing approach to examine the efficacy of visibility augmentation of atmospheric for precise moving object recognition. The study and its results show that detection algorithms more closely reflect the fundamental properties of moving objects in terms of pixel-oriented binary masks by using effective augmentation, even when the weather or atmosphere is terrible.

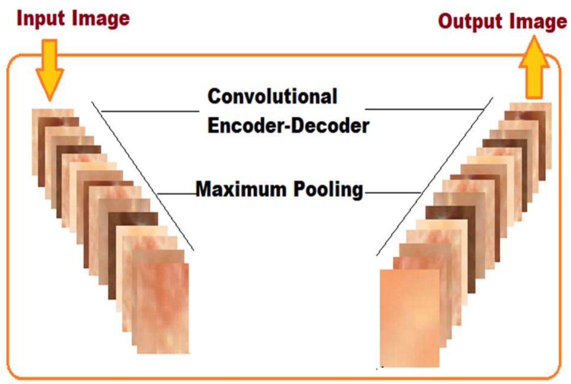

Figure 7. SegNet

L. Zhu et al. [18] demonstrate that one well-liked graph model for picture segmentation is the Normalized Cut (NCut) model. However, it has over-normalization, making it less effective in segmenting small objects and twigs. This study proposes the Explored Normalized Cut (ENCut) model, which uses a meaningful loop and a k-step random walk to create a balancing graph model that lowers the energy of a tiny prominent area to improve small object segmentation. A novel Random Walk Refining Term (RWRT) ENCut model refine that employs an unsupervised random walk to increase the model's local attention, enhancing the twig segmentation—a move-based technique designed to solve the ENCut model with RWRT efficiently. Data from three benchmark datasets show that our model outperforms other NCut-based segmentation methods and approaches state-of-the-art performance.

Z. Liu et al. [19] described that video object segmentation (VOS) is identifying and isolating a small number of objects in motion throughout a video sequence, with the first frame annotated to specify these items. Many currently available semi-supervised VOS algorithms take into account the optical flow to enhance the segmentation precision. However, due to the high complexity of visual flow estimates, semi-supervised VOS algorithms based on optical flows cannot operate in real-time. The use of a FAMINet comprises four separate networks: a feature extraction network (F), an appearance network (A), a motion network (M), and an integration network (I). The appearance network provides a first segmentation result on objects' static appearances. The motion network estimates the optical flow using a few parameters, which are quickly adjusted using a learning process called relaxed steepest descent, which runs in real-time online. The integration network fine-tunes the actual segmentation result.

Background initialization, foreground detection, and deep learning features use CNNs. Background model training benefits from convolutional neural networks (CNNs). Moving object segmentation suggests that deep learning updates models in changing environments. A DNN that reliably recognizes a webcam-captured object moving in 3D space. End-to-end depth sequence learning for moving object identification. It emphasizes foreground-background pixel-wise separation learning—spatial-temporal video segmentation. A novel background subtraction uses an end-to-end deep learning architecture—fully convolutional neural network-based unseen video backdrop removal. The network receives the current frame, two background frames at different time scales, and their semantic segmentation map.
To improve foreground-background contrast. The standard dataset experiments indicate that deep learning-based approaches affect pixel separation in the foreground and background. Most deep-learning video object identification systems need supervision. These approaches intensively test the availability of video frames during training, which may result in suboptimal detection results on certain more extended test sets.

Table 5: Comparison of Algorithms on Remote Sensing Satellite Image Processing Techniques and Image Classification

S.I No.	Specialization	Author[Ref.],year	Algorithm	Advantages	Setback
1	Spectral Resolution	J. zhoo et al.,[20], 2016	Conditional Random field	Overcomes spatial variability problem	Fail to use spatial location cues information
2	Radiometric Resolution	E. Nova et al.[21], 2013	Near Fiel Tech- nique	Suitable for close range applications	More error rate
3	Radiative Transfer Model	M. yeomet al.,[22], 2016	Radiometric Enhancement	Negligible BRDF effect	Depends on swath overlap
4	TSVD	F. lenti et al.,[23], 2014	Spatial Enhancement	Reduced noise level	Issue in selection of truncation parameter
5	Spectral un mixing algorithm	M. aimebendani et al.,[24], 2014	Spectral Enhancement	Low spectral distortion	fails to fuse different reso lution images
6				Better	

	Gabour Filter and Mean Shift classification	M. Espinola et al.,[25], 2016	Gabour Filter and Mean Shift algo-rithm	classification result for variable land cover type	Less accuracy for variable texture surface
7	POK classification	T. Mei al.,[26], 2015	POK	High computational efficiency	Less accuracy for panchromatic images
8	TS-MRF classification	S. Kraft et al.,[27], 2014	TS-MRF	Better performance than unsupervised technique	Fail to model non – stationary property

IV. Remote Sensing Satellite Image Applications

Agriculture, forestry, geology, hydrology, sea ice, land cover mapping, oceans, and coasts are only a few of the primary remote sensing satellite image applicattions.

Agriculture: Images captured from the air are used to determine the crop's overall health. It also involves keeping an eye on how farms are run.

Forestry: Remote sensing is used for a variety of forestry-related purposes, including ecological research, industrial forestry, and survey mapping. As a tool, remote sensing helps government agencies in charge of national forests and the environment achieve their goals. For example, we'll be assessing biophysical features and updating our data on forest cover. Industrial forest uses include counting trees, counting plants, and measuring biomass metrics. It also means keeping an eye on the forest's overall health, size, and mix of species.

Geology: Structural mapping, litho logical mapping, and rock mapping are just a few examples of the types of geological characteristics that may be mapped with the use of remote sensing. It is also put to use in the process of determining the make-up of land surfaces.

Hydrology: Radar imaging's active sensing skills are useful in hydrological research. Drainage basin mapping, flood mapping, and watershed and irrigation modeling are all a part of this process. This information to make educated guesses about the amount of water in the soil, the depth of the snow cover, and the water content of snow.

The Freezing of the Ocean: Tracking massive passages that are large enough to sail through requires the use of remote sensing data. It aids in meteorological and worldwide change studies by providing estimates of ice concentration, ice type, age, velocity, iceberg detection, and tracking. Alterations in Vegetation and the Use of

Land: Maps of land usage and land cover may be created using remote sensing methods. Understanding land use and land cover helps with protecting wildlife, managing natural resources, and keeping an eye on farming and city life.

Mapping: Mapping using radar data is the foundation of every remote sensing project. Digital Elevation Models (DEMs), which show how the Earth's surface slopes, are a key part of this. Also included are topographic maps and themed maps.

Mapping the Seas and the Coast: Remote sensing techniques, especially those used to predict storms and find ocean patterns, make it possible to map and keep track of how the ocean and coastal environment is changing over time.

V. Conclusion

In this study, provided a brief introduction to the topic of satellite image preprocessing, like image filtering, enhancement, thresholding, segmentation, and classification. Further, numerous articles indicated that various issues related to image preprocessing covered segmentation and classification approaches. The information acquired from this study helps to make future satellite image preprocessing, segmentation and classification models.

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