2022 IEEE International Conference for Women in Innovation, Technology & Entrepreneurship (ICWITE) | 978-1-6654-6490-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICWITE57052.2022.10176247

Panoptic Image Segmentation through Unet combined with Melody Search Optimization Algorithm for the Realistic Scene Image Understanding

Berlin Shaheema S
Department of Computer Science and Engineering
National Institute of Technology
Silchar,Assam,India
berlin21_rs@cse.nits.ac.in

Naresh Babu Muppalaneni
Department of Computer Science and Engineering
National Institute of Technology
Silchar,Assam,India
nareshmuppalaneni@gmail.com

***Abstract*—Realistic Scene understanding is a challenging task by recognizing instances along with the semantic scene. This work, efficient panoptic image segmentation through a deep UNet combined with the melody search optimization algorithm for realistic scene images understanding. The visually appealing things have a variety of constituent pieces that capture the unintended organisational linkages between the crucial components of the carefully considered objects and, as a result, group them altogether according to a perceptual organisation model.The melody search optimization algorithm reduces the Unet parameters, thereby improving the accuracy, UNet combines semantic and instance segmentation predictions to form panoptic predictions and reduces the computational time and memory resources. Hence,the scene understanding is performed without requiring knowledge of the physically inspiring things in advance. Our approach is evaluated on four challenging benchmarks: Mapillary Vistas, Indian Driving Dataset, KITTI, and cityscapes. The results show that our method performs better than the current state-of-the-art methodologies for comprehending scene photos.The performance of the presented method was assessed utilizing panoptic quality metrics and computational time.**

***Index Terms*—Panoptic Segmentation, Instance Segmentation, Scene Understanding, Unet, Melody Search**

I. Introduction

Computer vision enables computers and systems to extract useful information from digital photos, videos, and other visual inputs [1], [2]. Image segmentation is regarded as a challenging job in the fields of autonomous vehicles [3], computer vision, image-search engines, and machine learning [4] , and real-world applications [5] . The empirical nature of the conventional methods allows us to articulate the segmentation problem as an optimization problem by validating an objective criterion. The ambition of an optimization problem is to discover an approximation for the variables that maximize or minimize the fitness function and fulfills the limitations.

In general, objects in natural can be categorized into two: things and stuff [6], [7]. Things are therefore countless objects, like buildings, humans, vehicles, trafc signals and so on is the category that contains instance-level descriptions. Stuff, on the other hand, are traditional collection of salient items, that are not usually counted, such as the sky, roads, trees, seas, mountains, categories without instance-level descriptions. Two crucial tasks in image recognition are instance segmentation and semantic segmentation [8]. Examining things comes beneath an object recognition and instance segmentation [9], whereas considering stuff comes beneath semantic segmentation. The name encoding of pixels in panoptic segmentation involves distributing every pixel of an image to two names, the semantic label and the other, for instance, id. The pixels having a comparable label are considered to have their place in a similar class, and instance id for stuff is overlooked.

Panoptic Segmentation (PS) integrates the predictions from instance and semantic segmentation to produce a single, general output.Panoptic image segmentation is challenging because of the wide intra-class variation and intricate spatial organisation within a typical picture [10], [11]. Instance segmentation, which recognises and segments each instance of an object, and semantic segmentation, which tags each pixel with a class, are combined in panoptic segmentation. Each pixel in the image is given a semantic categorising label by PS, which also distinguishes the recurrence of a certain class.

This paper's primary contribution is a perceptual organization model (POM) based deep U-Net network combined with melody search optimization algorithm for image scene understanding. In order to capture non-random structural linkages between the essential components of ordered things, POM quantitatively integrates a number of Gestalt laws. The borders of various prominent structured objects in various outdoor situations are found using this U-Net model. Melody search optimization algorithm reduces the U-Net parameters, thereby improving the accuracy, U-Net combines semantic, and instance segmentation predictions to form panoptic predictions and reduce the computational time and memory resources. According to preliminary findings, our method outperforms two state-of-the-art research [12]–[14], [15] on four interesting image databases composed of different outdoor scenes and object classes.

The rest of this work is organized as follows. Section 2 describes the relevant works. In Section 3, the Deep U-Net, Melody search optimization technique is introduced. The training and inference techniques for comprehending scene photos are presented in Section 4. Section 5 presents the findings and considerations. Section 6 draws a conclusion in the end.

II. Related Works

Semantic segmentation and instance segmentation problems are combined in the recently recognised scene understanding challenge known as Panoptic segmentation. By integrating semantic segmentation and instance segmentation to encompass both stuff and thing classes, Krilov *et al.,* pioneered panoptic segmentation [16]. They assessed the effectiveness of their image segmentation demonstration using a brand-new panoptic quality metric (PQ). Using two 3x3 convolution layers based on FPN, Mask-RCNN for instance segmentation branch, and RPN feature maps from Mask-RCNN, stacked for semantic segmentation,with an end-to-end network for panoptic segmentation by Liu*et al.,* [16], [17]. The transformer neural network has been applied in [40]to forecast the missing features.

Kirillov *et al.,* suggest a panoptic feature pyramid network [19], a strategy to utilize the FPN features for semantic segmentation. De Geus *et al.,* presented a single network panoptic segmentation for street understanding [20]. Xiong*et al.,* addresses a unified panoptic segmentation network (UPSNet) [21], [22] to deal with panoptic segmentation. They used ResNet and FPN based Mask R-CNN to extract a convolutional feature maps. The instance segmentation subnetwork has three branches for segmentation, classification, and bounding box regression, [23] , [24].

Andra Petrovai *et al.,* proposed a trainable end-to-end multitasking network [25]for panoptic segmentation with object occlusion and depth ordering of scene. The feature pyramid network serves as the backbone of Li *et al.,* attention-guided .'s unitary network for panoptic segmentation (AUNet), which is further subdivided into a background branch, region proposal network branch, and foreground branch. Mohan et al. [26] offered an Efficient Panoptic Segmentation (Efficient PS) architecture containing a common backbone that properly encodes and fuses semantically rich multi-scale characteristics . In [27], [28], the image downsampling and upsampling are done with wavelet for extracting the image features.

Hou, Rui, et al. [29] presented a Real-Time Panoptic Segmentation from dense detections, that affects dense detection and a global self-recognition mechanism that works in a performance aware real-time environment. Lazarow, Justin, et al. [30] presented a learning instance occlusion method for panoptic segmentation. Occlusion is cheap, but especially effective in the fusion of instance process.

One of the main problems of panoptic image segmentation identified from previous studies is that the results of instance and semantic segmentation results are combined to give the panoptic output. Also, the complexity of this method increases the amount of calculations and the processing time. Current research explores simpler method for segmenting images of multiple scenes. Image annotation is done by a POM-based model without any object-specific knowledge. Also, the presented method consume less computations, resulting in faster processing time.

III. Perceptual based UNet combined with Melody Search Algorithm

Panoptic image segmentation algorithm for outdoor visual scenes using a UNet architecture in combination with a melody search algorithm is being investigated. Our study's objective is to explore foreground and background object boundaries based only on a generic characteristics of actual objects, such as perceptual association law, with a list of Gestalt cues [32] [31]. The primary contribution of this study is an image segmentation technique that draws inspiration from a POM, UNet with melody search. In comparison to other convolutional neural networks, the U-Net network is fully convolutional and requires a smaller training set to achieve the same level of segmentation accuracy [34], [33]. The competition here is to divide an established set of parts of structured objects assembled into domains and classify the objects by naming them in a learning approach [35], [36].

A. Data Preprocessing and Augmentation

Data augmentation is a method for accelerating the training of machine learning models in deep architectures by accelerating convergence. Typically, it entails performing a number of transformations in the feature spaces, the data space, or both. This kind of augmentation modifies the existing data to create new illustrations. There are many other types of transformations that can be used, including cropping, rotations, warping, scaling, and colour space changes. The goal of these transformations is to produce more samples to expand the dataset, avoid over-fitting and perhaps normalise the model, possibly balance the classes in the database, and even produce new samples in an unnatural way that are more suited to the task at hand.

B. UNet network

U-Net [37] is a U-shaped network with contraction path and an expansion path. A diminishing path is used to preserve perspective information, whereas the expansive path is used for precise information.The panoptic segmentation using the UNet architecture includes a contraction and expansion paths. The contraction path is composed of two consecutive 3 X 3 convolutions in each step, followed by max-pooling with ReLU non-linearity utilising 2 X 2 windows in stride 2. The spatial information is reduced while the highlight data is enhanced during the contraction.

U-Net's main contribution to the augmentation pass consists of feature map upsampling followed by 2×2 convolution ("upconvolution"), which halves the number of feature channels. The feature map and the corresponding clipped

978-1-6654-6490-1/22/$31.00 ©2022 IEEE

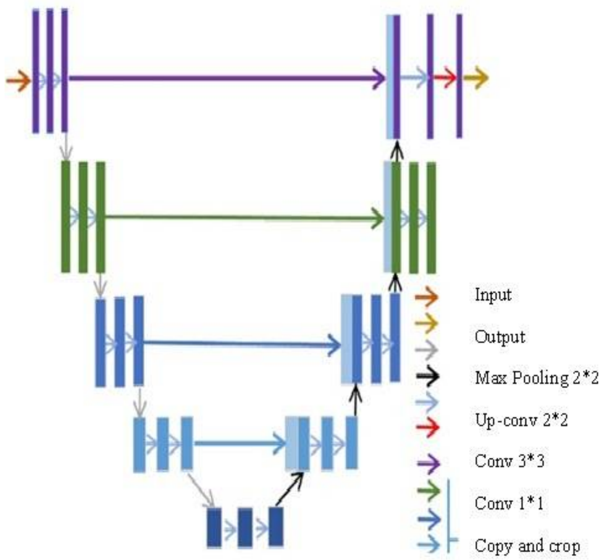


Fig. 1. The U-Net network structure

feature map from the contraction path are now concatenated. The ReLU non-linearity is then applied, followed by two successive 3 x 3 convolution operations. Therefore, the broad pathway combines characteristics and spatial data for precise panoptic segmentation. The final layer uses 1x1 convolution to map the feature vectors of each 16x16 component to the desired number of classes.

U-Net presents a new approach to solve this information loss problem. It sends information to every upsampling layer in expanding path from the corresponding downsampling layer in the contracting path to gather more precise information while keeping the computations low. Since the cover contains a lot of information at the start of the erosion pass, providing matching details in the input image helps the upsampling process expand the pass, greatly improving the results.

In contrast to grouping, where only the final result of very deep networks is important, panoptic segmentation involves not only pixel-level recognition, but also transferring the features learned at various steps of the encoder to lettering in pixel space. You also need a mechanism. transfer. Finally, panoptic segmentation achieves fine-grained semantics by making fine-grained predictions that understand the label of each pixel such that each pixel is classified into a class of surrounding objects or regions [38]

C. Melody Search Algorithm

Ashrafi and Dariane (2011) [39], [40] proposed Melody search (MeS) algorithm a group improvisation method. To determine the ideal pitch order in a tune, it simultaneously uses many memories, collectively referred to as player memory (PM). The following are the main steps of MeS.

Step 1: Initialize N random Unet to generate the image memories of Unet based on the maximum and minimum bound of the imaging dimensions. The optimization parameters employed are specifically number of image pixels (I_M), image pixel size (I_{MS}), the maximum iterations (I_N), maximum number of iterations for the initial phase (I_{NI}), bandwidth (B), and image memory rate (I_{MR}) respectively. Train all the Unet panoptic quality is considered. Assign hyper parameters to all the Unet.

Step 2: The initial phase comprises of two repeated ways which are to update each IM and improve a new labelled panoptic picture from each IM, until the INI measure is fulfilled.

(1) Initialize MM as described via Eq. 1:

$$MM = \lfloor IM_1, IM_2....IM_{PMN} \rfloor \tag{1}$$

where MM stands for the melodic dimension that a collection of image memories is a part of. The matrix of the ID is produced by Eqs. 2 and 3, respectively.

$$ID_i = \begin{bmatrix} x_{i,1}^1 & x_{i,1}^2 & ... & ... & x_{i,1}^D \\ x_{i,}^1 & x_{i,2}^2 & ... & ... & x_{i,2}^D \\ : & & & & \\ : & & & & \\ x_{i,PMS}^1 & x_{i,PMS}^2 & ... & ... & x_{i,PMS}^D \end{bmatrix} \begin{matrix} Fit_i^1 \\ Fit_i^2 \\ : \\ : \\ Fit_i^{PMS} \end{matrix} \tag{2}$$

$$x_{i,j}^k = LB_k + r.(UB_k - LB_k) \tag{3}$$

$$for \begin{cases} i = 1, 2, ...I_M \\ j = 1, 2, ...M_S \\ k = 1, 2, ...D_l \end{cases}$$

where D is the total number of decision variables, $[LB_k + UB_k]$ of the examining dimension, and r are uniformly distributed in 0; 1

2)Improve a new pixel intensity X

$$X_{i,new} = \left(X^1{}_{i,new}, X^2{}_{i,new}....X^n{}_{i,new}\right) \tag{4}$$

from each PM according to three rules. Pixel consideration: The value selected from any specified P_M for each pixel variable. Intensity adjustment: The value can be calculated using an intensity adjusting rate (I_AR) and constant pitch band-width (B) such as those found in Eqs. 5

$$IAR_t = IAR_{min} + \frac{IAR_{min} - AAR_{min}}{NI} \times t \tag{5}$$

where image adjusting rate denoted as (IARt) of the ith iteration,the minimum adjusting rates and maximum adjusting rates represented as (IARmin,IARmax), respectively, and maximum number of iterations (NI).

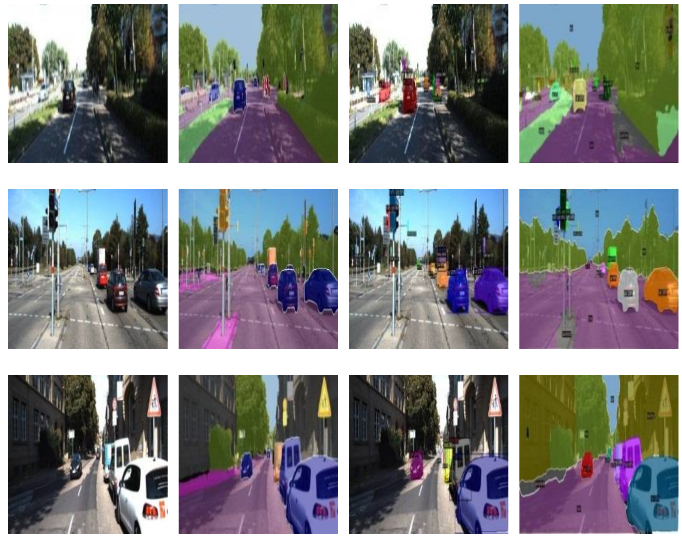
Randomization: : Increases the variety of the solution. (3) Update every IM.

Step 3: This is the second phase, which contains two iterative steps until the IN is satisfied. (1) Create a new pixel from each IM using the range of pixels. (2) Update every IM. (3) At last, conclude the potential pixel ranges for the next improvement.

978-1-6654-6490-1/22/$31.00 ©2022 IEEE

(a) (b) (c) (d)

Fig. 2. Street Scene understanding of Indian driving Dataset a) Input Image b) Semantic Segmentation c) Instance Image Segmentation d) panoptic image segmentation.



(a) (b) (c) (d)

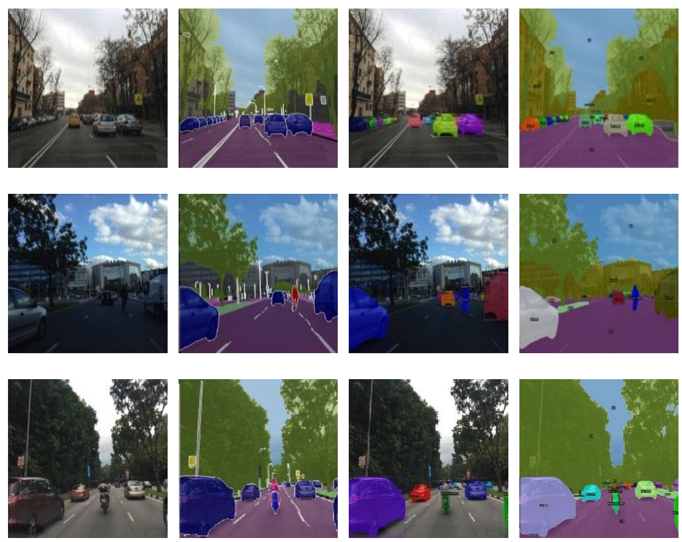
Fig. 3. Street Scene understanding of KTTI Dataset a) Input Image b) Semantic Segmentation c) Instance Image Segmentation d) panoptic image segmentation

IV. Experimental Results

In this work, the whole test image dataset is taken from the four public datasets with semantic and instance segmentation annotations: Cityscapes [14], KITTI [15],Mapillary Vistas [13] ,and Indian Driving Dataset [16] is employed. Cityscapes comprise 5k street scene images taken in German cities. There are 8 classes and 11 classes of panoptic annotation. All images are 1024 x 2048 pixels in size. KITTI contains a set of visual tasks created using an autonomous driving platform. Mapillary Vistas consists of 25,000 images from street scenes. All images were taken at various locations around the world and contain 37 classes and 28 classes of panoramic annotation. The image resolution is very high, normal resolution is 2481 x 3419 pixels. IDD [18] contains 10,003 images from 182 driving sequences split into 6,993/981/2,029 images for training, validation, and testing. Records are annotated with 26 classes (17 items and 9 instance-specific).

The presented Perceptual-based UNet combined with Melody Search Algorithm was implemented in a desktop computer with an Intel Core i3 processor, tenth generation (3.6 GHz) CPU, 8.0 GB RAM, and NVIDIA GPU. Implementation of our methodology is done using TensorFlow for training; optimization using a melody search optimizer with a momentum of 0.9. These weights are found empirically and normalization is realistic with a weight decay of 0.9.

The optimization problem measured in this paper is to explain the panoptic color image segmentation problem using Perceptual based UNet combined with Melody Search Algorithm. Our objective is to improve the objective function in order to differentiate the substances by decreasing the pixels in the edges value and overall deviation. The performance of IS using our algorithm is authorized by applying it to numerous natural images. The presented method is evaluated both qualitatively and quantitatively. In the qualitative evaluation, the panoptic image output along with instance and semantic image segmentation is presented.



(a) (b) (c) (d)

Fig. 4. Street Scene understanding of Mapillary Vistas Dataset a) Input Image b) Semantic Segmentation c) Instance Image Segmentation d) panoptic image segmentation.

Figures 2, 3, and 4 show chromatic results such as semantic and panoptic segmentation for the Indian driving dataset.Particularly for large objects, the instance mask from the instance segmentation header has imprecise limits. Nevertheless, performance in recognition and categorization is strong. In comparison to the instance mask in the instance

978-1-6654-6490-1/22/$31.00 ©2022 IEEE

TABLE I
PANOPTIC QUANTITATIVE ANALYSIS WITH COMPARED METHODS

Method	Dataset	PQ	SQ	RQ	PQ^{TH}	PQ^{ST}	AP	mIoU
Panoptic Deeplab	Vista	65.5	77.8	75.2	56.5	72.0	30.2	41.7
	Cityscapes	57.6	74.9	54.7	39.5	61.8	49.9	58.4
	KITTI	47.7	75.2	57.1	32.9	55.1	29.9	58.4
	IDD	65.9	82.7	80.7	68.6	63.9	33.3	53.5
EfficientPS	Vistas	66.4	83.5	78.8	59.3	71.5	44.3	52.4
	Cityscapes	63.5	72.8	74.2	59.5	74.0	32.2	43.7
	KITTI	43.7	73.2	54.1	30.9	53.1	27.9	56.4
	IDD	51.1	78.8	63.5	52.6	50.3	32.97	72.1
Seamless	Vistas	57.6	74.9	54.3	39.8	61.8	49.9	58.4
	Cityscapes	58.5	68.5	57.9	48.97	47.9	33.7	81.8
	KITTI	46.4	67.7	58.7	53.5	52.8	31.4	91.6
	IDD	48.5	78.5	61.9	49.5	47.9	29.4	69.3
Proposed Method	Vistas	47.6	58.9	74.57	51.8	63.7	34.6	75.1
	Cityscapes	51.1	78.8	63.5	52.6	50.3	32.9	72.1
	KITTI	43.7	73.2	54.1	30.9	53.1	27.9	56.4
	IDD	48.5	78.5	61.9	49.5	47.9	31.4	71.3

TABLE II
HUMAN VS MACHINE PERFORMANCE OF VARIOUS DATASET

Method	Dataset	PQ	SQ	RQ	PQ^{ST}	PQ^{TH}
CITYSCAPES	HUMAN	69.6	84.1	82.1	71.2	67.4
	MACHINE	61.2	81.0	74.4	66.4	54.1
ADE20K	HUMAN	67.6	85.7	78.6	71.0	66.4
	MACHINE	55.6	74.4	43.27	24.5	41.1
VISTASs	HUMAN	57.7	79.7	71.6	62.7	53.6
	MACHINE	48.3	73.6	47.7	41.8	35.7
IDD	HUMAN	65.9	82.7	80.7	68.6	63.9
	MACHINE	53.5	77.8	44.3	62.7	43.4

segmentation header, the instance mask in the panoptical segmentation image is more accurate and better aligned with the object. This is due to the fact that it provides additional context and background details. Additionally, additional mask caution data enhances background classification.

The evaluation of the various datasets from Tables 1 and 2 validates the visual results. Table 1 displays various methodologies and datasets panoptic quality metrics, including panoptic quality (PQ), segmentation quality (SQ), and recognition quality (RQ). The effectiveness of instance segmentation and object detection were measured by their respective average precisions (AP). The effectiveness of semantic segmentation is gauged by the mIoU mean Intersection over Union. The PQ metrics for things and stuff are denoted by PQ^{th} and PQ^{st}, respectively.

The performance of humans and machines is seen in Table 2. The regularity of the datasets under consideration is substantially higher than machine performance. The numerous parameters also show the total performance disparity between humans and machines. RQ explicitly falls within this category, whereas SQ is closer.

V. CONCLUSION

A panoptic image segmentation algorithm for shared natural scene image understanding is presented for viewing finer-grained regions that uses panoptic segmentation. Our main contribution is working with UNet to develop a POM combined with the Melody Search algorithm. Experimental results shows that the presented method outperforms rival approaches and provides outstanding segmentation quality on four challenging scene image datasets. Qualitative and quantitative evaluation results demonstrate that our approach has improved the detection of scenes and instances in images in combination with state-of-the-art image segmentation approaches. Our study provides new insights to scientists and practitioners on how to improve captioning.

REFERENCES

[1] BALLARD DH. Ballard D. And Brown CM 1982 Computer Vision. Image;17:2–2.

[2] Babu, R. Venkatesh, Mahadeva Prasanna, and Vinay P. Namboodiri, eds. Computer Vision, Pattern Recognition, Image Processing, and Graphics: 7th National Conference, NCVPRIPG 2019, Hubballi, India, December 22–24, 2019, Revised Selected Papers. Vol. 1249. Springer Nature, 2020.

[3] Sonka M, Hlavac V, Boyle R. Image processing, analysis, and machine vision. Cengage Learning; 2014.

[4] Chen C, Seff A, Kornhauser A, Xiao J. Deepdriving: Learning affordance for direct perception in autonomous driving. In: Proceedings of the IEEE international conference on computer vision; 2015. p. 2722–2730.

[5] Geiger A, Lenz P, Urtasun R. Are we ready for autonomous driving? the kitti vision benchmark suite. In: 2012 IEEE conference on computer vision and pattern recognition IEEE; 2012. p. 3354–3361.

[6] Shah SK. Performance modeling and algorithm characterization for robust image segmentation. International Journal of Computer Vision 2008;80(1):92–103.

[7] Adelson EH. On seeing stuff: the perception of materials by humans and machines. In: Human vision and electronic imaging VI, vol. 4299 SPIE; 2001. p. 1–12.

[8] de Geus, D., Meletis, P., Dubbelman, G. (2019, June). Single network panoptic segmentation for street scene understanding. In 2019 IEEE Intelligent Vehicles Symposium (IV) (pp. 709-715). IEEE.

[9] Li J, Raventos A, Bhargava A, Tagawa T, Gaidon A. Learning to fuse things and stuff. arXiv preprint arXiv:181201192 2018;.

[10] Petrovai A, Nedevschi S. Efficient instance and semantic segmentation for automated driving. In: 2019 IEEE Intelligent Vehicles Symposium (IV) IEEE; 2019. p. 2575–2581.

[11] Fong WK, Mohan R, Hurtado JV, Zhou L, Caesar H, Beijbom O, et al. Panoptic nuscenes: A large-scale benchmark for lidar panoptic segmentation and tracking. IEEE Robotics and Automation Letters 2022;7(2):3795–3802.

[12] Yao L, Chyau A. A unified neural network for panoptic segmentation. In: Computer Graphics Forum, vol. 38 Wiley Online Library; 2019. p. 461–468.

[13] Neuhold G, Ollmann T, Rota Bulo S, Kontschieder P. The mapillary vistas dataset for semantic understanding of street scenes. In: Proceedings of the IEEE international conference on computer vision; 2017. p. 4990–4999.

[14] Cordts M, Omran M, Ramos S, Rehfeld T, Enzweiler M, Benenson R, et al. The cityscapes dataset for semantic urban scene understanding. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 3213–3223.

[15] Geiger A, Lenz P, Stiller C, Urtasun R. Vision meets robotics: The kitti dataset. The International Journal of Robotics Research 2013;32(11):1231–1237.

[16] Varma G, Subramanian A, Namboodiri A, Chandraker M, Jawahar C. IDD: A dataset for exploring problems of autonomous navigation in unconstrained environments. In: 2019 IEEE Winter Conference on Applications of Computer Vision (WACV) IEEE; 2019. p. 1743–1751.

[17] Kirillov A, He K, Girshick R, Rother C, Dollár P. Panoptic segmentation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2019. p. 9404–9413.

[18] Sekar K., Suganya Devi K., Satish Kumar Satti, Srinivasan P. and Sivaji Bandyopadhyay, ”Pragmatic Prospects of Machine Learning in Compressed Data Recovery for WSNs”, unpublished.

[19] Liu H, Peng C, Yu C, Wang J, Liu X, Yu G, et al. An end-to-end network for panoptic segmentation. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition; 2019. p. 6172–6181.

[20] Wang H, Zhu Y, Adam H, Yuille A, Chen LC. Max-deeplab: End-to-end panoptic segmentation with mask transformers. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition; 2021. p. 5463–5474.

[21] de Geus D, Meletis P, Dubbelman G. Single network panoptic segmentation for street scene understanding. In: 2019 IEEE Intelligent Vehicles Symposium (IV) IEEE; 2019. p. 709–715.

[22] Weng, L., Wang, Y., Gao, F. (2022). Traffic Scene Perception Based on Joint Object Detection and Semantic Segmentation. Neural Processing Letters, 1-17.

[23] Xiong Y, Liao R, Zhao H, Hu R, Bai M, Yumer E, et al. Upsnet: A unified panoptic segmentation network. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2019. p. 8818–8826.

[24] Petrovai A, Nedevschi S. Fast Panoptic Segmentation with Soft Attention Embeddings. Sensors 2022;22(3):783.

[25] Garcia-Garcia A, Orts-Escolano S, Oprea S, Villena-Martinez V, Martinez-Gonzalez P, Garcia-Rodriguez J. A survey on deep learning techniques for image and video semantic segmentation. Applied Soft Computing 2018;70:41–65.

[26] Petrovai A, Nedevschi S. Multi-task network for panoptic segmentation in automated driving. In: 2019 IEEE Intelligent Transportation Systems Conference (ITSC) IEEE; 2019. p. 2394–2401.

[27] K. Sekar, K. Suganya Devi, P. Srinivasan and V. M. SenthilKumar, ”Deep Wavelet Architecture for Compressive sensing Recovery,” 2020 Seventh International Conference on Information Technology Trends (ITT), 2020, pp. 185-189, doi: 10.1109/ITT51279.2020.9320773.

[28] Sekar, K., Devi, K.S., Srinivasan, P., Dheepa, T. (2022). Deep Wavelet-Based Compressive Sensing Data Reconstruction for Wireless Visual Sensor Networks. In: Das, K.N., Das, D., Ray, A.K., Suganthan, P.N. (eds) Proceedings of the International Conference on Computational Intelligence and Sustainable Technologies. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-16-6893-7_31.

[29] Mohan R, Valada A. Efficientps: Efficient panoptic segmentation. International Journal of Computer Vision 2021;129(5):1551–1579.

[30] Hou R, Li J, Bhargava A, Raventos A, Guizilini V, Fang C, et al. Real-time panoptic segmentation from dense detections. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2020. p. 8523–8532.

[31] Lazarow J, Lee K, Shi K, Tu Z. Learning instance occlusion for panoptic segmentation. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition; 2020. p. 10720–10729.

[32] Cheng, Chang, et al. ”Outdoor scene image segmentation based on background recognition and perceptual organization.” IEEE transactions on image processing 21.3 (2011): 1007-1019.

[33] Suganya Devi, K., Sekar, K., Singh, N., Baroi, S.J., Sah, D.K., Borahi, K. (2022). Detection of Abnormalities in Mammograms Using Deep Convolutional Neural Networks. In:

[34] Das, K.N., Das, D., Ray, A.K., Suganthan, P.N. (eds) Proceedings of the International Conference on Computational Intelligence and Sustainable Technologies. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-16-6893-7_37.

[35] Elharrouss O, Al-Maadeed S, Subramanian N, Ottakath N, Al-maadeed N, Himeur Y. Panoptic segmentation: a review. arXiv preprint arXiv:211110250 2021;.

[36] Tian Z, Zhang B, Chen H, Shen C. Instance and panoptic segmentation using conditional convolutions. IEEE Transactions on Pattern Analysis and Machine Intelligence 2022;.

[37] Liu X, Hou Y, Yao A, Chen Y, Li K. CASNet: Common Attribute Support Network for image instance and panoptic segmentation. In: 2020 25th International Conference on Pattern Recognition (ICPR) IEEE; 2021. p. 8469–8475.

[38] Zendel O, Schörghuber M, Rainer B, Murschitz M, Beleznai C. Unifying Panoptic Segmentation for Autonomous Driving. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2022. p. 21351–21360.

[39] Ashrafi S, Dariane A. A novel and effective algorithm for numerical optimization: melody search (MS). In: 2011 11th international conference on hybrid intelligent systems (HIS) IEEE; 2011. p. 109–114.

[40] Xing, B., Gao, W. J. (2014). Innovative computational intelligence: a rough guide to 134 clever algorithms (Vol. 62, pp. 22-28). Cham: Springer international publishing.

978-1-6654-6490-1/22/$31.00 ©2022 IEEE