

# IROS 2019 Lifelong Robotic Vision Challenge

## Lifelong Object Recognition Report

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**Abstract**—This report summarizes IROS 2019-Lifelong Robotic Vision Competition (Lifelong Object Recognition Challenge) with methods and results from the top 8 finalists (out of over 150 teams). The competition dataset (L)ifel(O)ng (R)obotic V(IS)ion (OpenLORIS) - Object Recognition (OpenLORIS-object) is designed for driving lifelong/continual learning research and application in robotic vision domain, with everyday objects in home, office, campus, and mall scenarios. The dataset explicitly quantifies the variants of illumination, object occlusion, object size, camera-object distance/angles, and clutter information. Rules are designed to quantify the learning capability of the robotic vision system when faced with the objects appearing in the dynamic environments in the contest. Individual reports, dataset information, rules, and released source code can be found at the [project homepage](#).

### I. INTRODUCTION

Humans have the remarkable ability to learn continuously from the external environment and the inner experience. One of the grand goals of robots is also building an artificial “lifelong learning” agent that can shape a cultivated understanding of the world from the current scene and their previous knowledge via an autonomous lifelong development. It is challenging for the robot learning process to retain earlier knowledge when they encounter new tasks or information. Recent advances in computer vision and deep learning methods have been very impressive due to large-scale datasets, such as ImageNet [1] and COCO [2]. However, robotic vision poses unique new challenges for applying visual algorithms developed from these computer vision datasets because they implicitly assume a fixed set of categories and

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time-invariant task distributions [3]. Semantic concepts change dynamically over time [4]–[6]. Thus, sizeable robotic vision datasets collected from real-time changing environments for accelerating the research and evaluation of robotic vision algorithms are crucial. For bridging the gap between robotic vision and stationary computer vision fields, we utilize a real robot mounted with multiple-high-resolution sensors (e.g., monocular/RGB-D from RealSense D435i, dual fisheye images from RealSense T265, LiDAR,, see Fig. 1) to actively collect the data from the real-world objects in several kinds of typical scenarios, like homes, offices,campus, and malls.

Lifelong learning approaches can be divided into 1) methods that retrain the whole network via regularizing the model parameters learned from previous tasks, e.g., Learning without Forgetting (LwF) [7], Elastic Weight Consolidation (EWC) [8] and Synaptic Intelligence (SI) [9]; 2) methods that dynamically expand/adjust the network architecture if learning new tasks, e.g., Context-dependent Gating (XdG) [10] and Dynamic Expandable Network (DEN) [11]; 3) rehearsal approaches gather all methods that save raw samples as memory of past tasks. These samples are used to maintain knowledge about the past in the model and then replayed with samples drawn from the new task when training the model, e.g., Incremental Classifier and Representation Learning (ICaRL) [12]; and generative replay approaches train generative models on the data distribution [13]–[15], and they are able to afterward sample data from experience when learning new data, e.g., Deep Generative Replay (DGR) [16], DGR with dual memory [17] and feedback [18].

This report summarizes IROS 2019-Lifelong Robotic Vision Competition (Lifelong Object Recognition challenge) with dataset, rules, methods and results from the top 8 finalists (out of over 150 teams). Individual reports, dataset information, rules, and released source codes can be found at the [competition homepage](#).

### II. IROS 2019 LIFELONG ROBOTIC VISION - OBJECT RECOGNITION CHALLENGE

This challenge aimed to explore how to leverage the knowledge learned from previous tasks that could generalize to new task effectively, and also how to efficiently memorize of previously learned tasks. The work pathed the way for

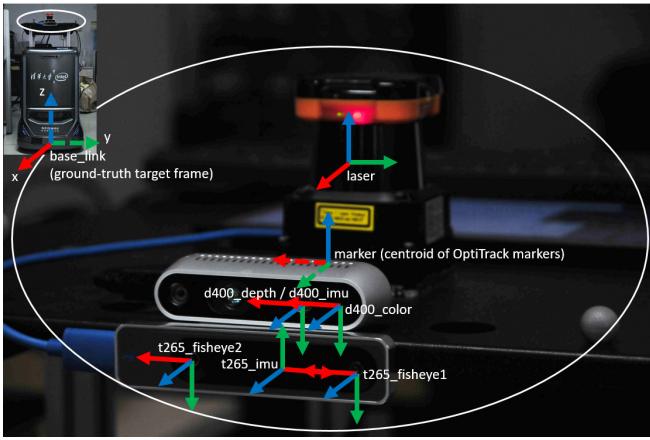


Fig. 1: OpenLORIS robotic platform (left) mounted with multiple sensors (right). In OpenLORIS-Object dataset, the RGB-D data is collected from the depth camera.

robots to behave like humans in terms of knowledge transfer, association, and combination capabilities.

To our best knowledge, the provided lifelong object recognition dataset OpenLORIS-Object-v1 [19] is the first one that explicitly indicates the task difficulty under the incremental setting, which is able to foster the lifelong/continual/incremental learning in a supervised/semi-supervised manner. Different from previous instance/class-incremental task, the difficulty-incremental learning is to test the model’s capability over continuous learning when faced with multiple environmental factors, such as illumination, occlusion, camera-object distances/angles, clutter, and context information in both low and high dynamic scenes.

#### A. OpenLORIS-Object Dataset

IROS 2019 competition provided the 1<sup>st</sup> version of OpenLORIS-Object dataset for the participants. Note that our dataset has been updated with twice the size in content available at the [project homepage](#) with detailed information, visualization, downloading instructions and benchmarks on SOTA lifelong learning methods [19].

We included the common challenges that the robot is usually faced with, such as illumination, occlusion, camera-object distance, etc. Furthermore, we explicitly decompose these factors from real-life environments and have quantified their difficulty levels. In summary, to better understand which characteristics of robotic data negatively influence the results of the lifelong object recognition, we independently consider: 1) illumination, 2) occlusion, 3) object size, 4) camera-object distance, 5) camera-object angle, and 6) clutter.

- 1). **Illumination.** The illumination can vary significantly across time, e.g., day and night. We repeat the data collection under weak, normal, and strong lighting conditions, respectively. The task becomes challenging with lights to be very weak.
- 2). **Occlusion.** Occlusion happens when a part of an object is hidden by other objects, or only a portion of the object

is visible in the field of view. Occlusion significantly increases the difficulty for recognition.

- 3). **Object size.** Small-size objects make the task challenging, like dry batteries or glue sticks.
- 4). **Camera-object distance.** It affects actual pixels of the objects in the image.
- 5). **Camera-object angle.** The angles between the cameras and objects affect the attributes detected from the object.
- 6). **Clutter.** The presence of other objects in the vicinity of the considered object may interfere with the classification task.

The version of OpenLORIS-Object for this competition is a collection of 69 instances, including 19 categories daily necessities objects under 7 scenes. For each instance, a 17 seconds video (at 30 fps) has been recorded with a depth camera delivering 500 RGB-D frames (with 260 distinguishable object views picked and provided in the dataset). 4 environmental factors, each has 3 level changes, are considered explicitly, including illumination variants during recording, occlusion percentage of the objects, object pixel size in each frame, and the clutter of the scene. Note that the variables of 3) object size and 4) camera-object distance are combined together because in the real-world scenarios, it is hard to distinguish the effects of these two factors brought to the actual data collected from the mobile robots, but we can identify their joint effects on the actual pixel sizes of the objects in the frames roughly. The variable 5) is considered as different recorded views of the objects. The defined three difficulty levels for each factor are shown in Table. I (totally we have 12 levels w.r.t. the environment factors across all instances). The levels 1, 2, and 3 are ranked with increasing difficulties.

For each instance at each level, we provided 260 samples, both have RGB and depth images. Thus, the total images provided is around 2 (RGB and depth)  $\times$  260 (samples per instance)  $\times$  69 (instances)  $\times$  4 (factors per level)  $\times$  3 (difficulty levels) = 430,560 images. Also, we have provided bounding boxes and masks for each RGB image with Labelme [20]. The size of images under illumination, occlusion and object pixel size factors is 424  $\times$  240 pixels, and the size of images under object pixel size factor are 424  $\times$  240, 320  $\times$  180, 1280  $\times$  720 pixels (for 3 difficulty levels). Picked samples have been shown in Fig. 2.

#### B. Challenge Phases and Evaluation Rules

We held 2 phases for the challenge. The preliminary contest we provided 9 batches of datasets which contain different factors and difficulty levels, for each batch, we have train/validation/test data splits. The core of this incremental learning setting is, we need the first train on the first batch of the dataset, and then 2<sup>nd</sup> batch, 3<sup>rd</sup> batch, until the 9<sup>th</sup> batch, and then use the final model to obtain the test accuracy of all encounter tasks (batches). The training/validation datasets can only be accessed during the model optimizations. We held the evaluation platform on [Codalab](#). There had been over 150 participants during the preliminary contest and we

Level	Illumination	Occlusion (percentage)	Object Pixel Size (pixels)	Clutter	Context	#Classes	#Instances
1	Strong	0%	$> 200 \times 200$	Simple	Home/office/mall	19	69
2	Normal	25%	$30 \times 30 - 200 \times 200$	Normal			
3	Weak	50%	$< 30 \times 30$	Complex			

TABLE I: Details of each 3 levels for 4 real-life robotic vision challenges.

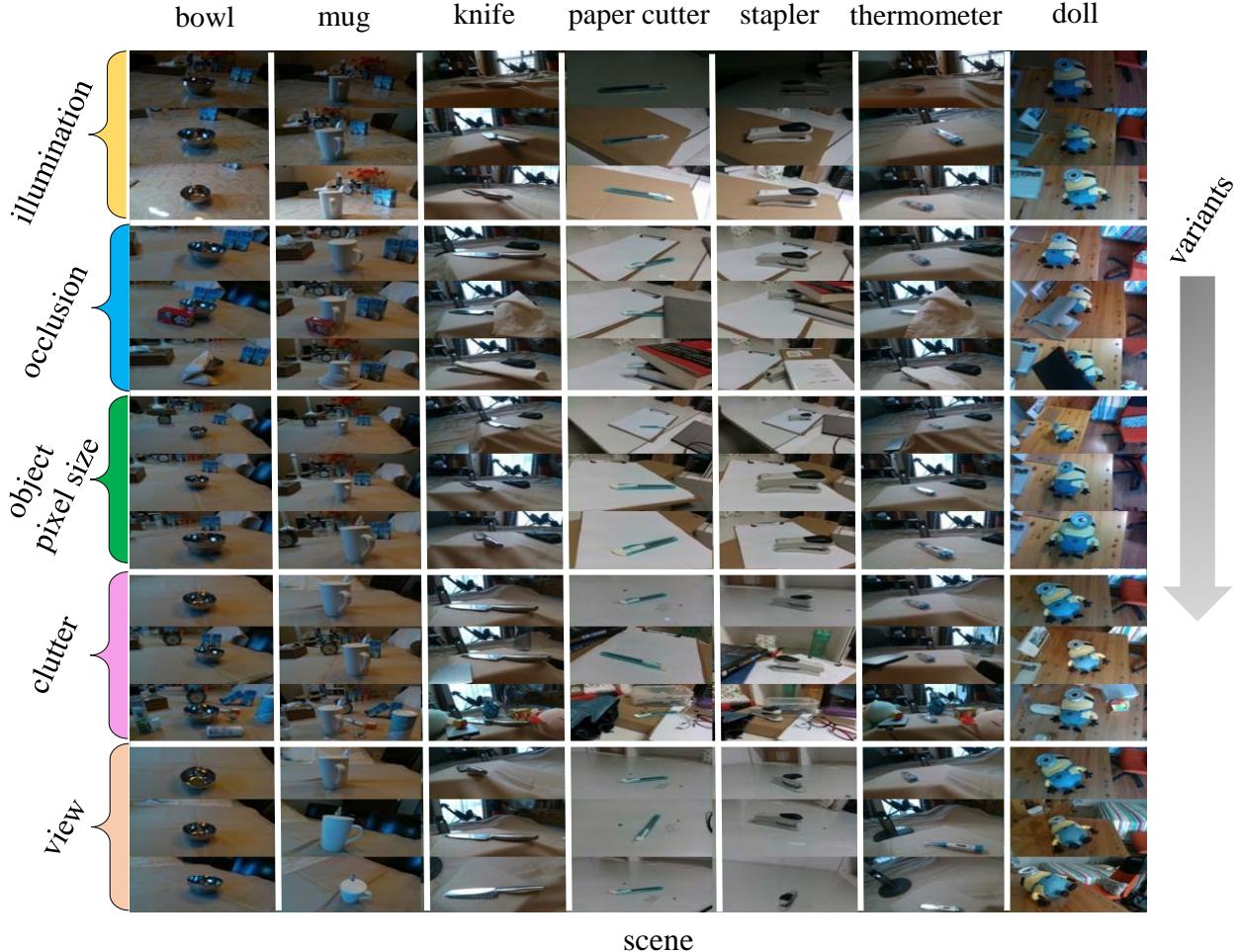


Fig. 2: Picked samples of the objects from 7 scenes (column) under multiple level environment conditions (row). The variants from top to bottom are illumination (weak, normal, and strong); occlusion (0%, 25%, and 50%); object pixel size ( $< 30 \times 30$ ,  $30 \times 30 - 200 \times 200$ , and  $> 200 \times 200$ ); clutter (simple, normal and complex); and multi-views of the objects. (Note that we use different views as training samples of each difficulty level in each factor).

chose 8 teams with higher testing accuracies over all testing batches as our finalists.

For the final round, different from standard computer vision challenge [1], [2], not only the overall accuracy on all tasks was evaluated but also the model efficiency, including model size, memory cost, and replay size (the number of old task samples used for learning new tasks, smaller is better) were considered. Meanwhile, instead of directly asking the participants to submit the prediction results on the test dataset as standard deep learning challenges [1], [2], the organizers received either source codes or binary codes to evaluate their whole lifelong learning process to make fair comparison. The finalists' methods were tested by the organizers on Intel Core i9 CPU and 1Nvidia RTX 1080 Ti GPU. For

final round dataset, we randomly shuffled the dataset with multiple factors. Data is split up to 12 batches/tasks and each batch/task samples are from one subdirectories (there are 12 subdirectories in total, 4 factors  $\times$  3 level/factor). Each batch includes 69 instances from 7 scenes, about 21520 test samples, 21,520 validation samples and 172,200 training samples. The metrics and corresponding grading weights are shown in Table II. As can be seen, we also provided a bonus test set which is recorded in under different context background with some deformation. The adaptation on this bonus testing data is a challenging task for our task.

TABLE II: Metrics and grading criteria for final round

Metric	Accuracy	Model Size	Inference Time	Replay Size	Oral Presentation	Accuracy on Bonus Dataset
Weight	50%	8%	8%	8%	10%	16%

### C. Challenge Results

From more than 150 registered participants, 8 teams entered in the final phase and submitted results, codes, posters, slides and abstract papers ([available here](#)). Table III reports the details of all metrics (except oral presentation) for each team.

**Architectures and main ideas:** All the proposed methods use end-to-end deep learning models and employ the GPU(s) for training. For lifelong learning strategies: 5 teams applied regularization methods, 2 teams utilized knowledge distillation methods and 1 team used network expansion method. 4 teams applied resampling mechanism to alleviate catastrophic forgetting. Meanwhile, some other computer vision methods including saliency map, Single Shot multi-box Detection (SSD), data augmentation are also utilized in their solutions.

## III. CHALLENGE METHODS AND TEAMS

### A. HIK.ILG Team

The team developed the dynamic neural network, which was comprised of two parts: dynamic network expansion for data across dissimilar domains and knowledge distillation for data in similar domains (See Figure 3). They froze the shared convolutional layers and trained new heads for new tasks. The domain gap was determined by measuring the accuracy of the previous model before training on current task. In order to increase the generalization ability of the trained model, they used ImageNet pre-trained model for the shared convolutional layers, and took more data augmentation and more batches to train head1 for base model. Without using previous data, they discovered known instances in current task by a single forward pass via previous model. Those correctly classified were treated as known samples. They used these samples for knowledge distillation. They utilized the best head over multiple heads for distillation, which is verified by experimental results.

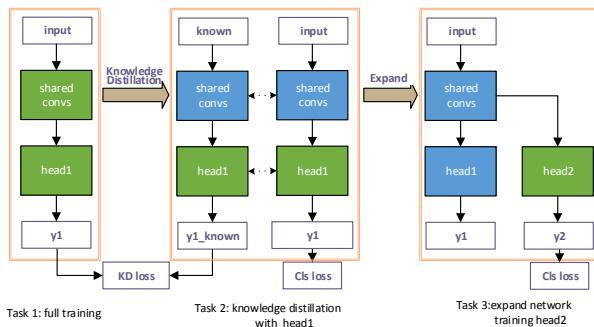


Fig. 3: The architecture of proposed dynamic neural network by HIK.ILG Team.

### B. Unibo Team

The team proposed a new Continual Learning approach based on latent rehearsal, namely the replay of latent neural network activation instead of raw images at the input level. The algorithm can be deployed on the edge with low latency. With latent rehearsal (see Figure 4) they denoted an approach where instead of maintaining in the external memory copies of input patterns in the form of raw data, they stored the pattern activation at a given level (denoted as latent rehearsal layer). The algorithm can be summarized as follow: 1) Take  $n$  patterns from the current batch; 2) Forward them through the network until the rehearsal layer; 3) Select  $k$  patterns from the rehearsal memory; 4) Concat the original and the replay patterns; 5) Forward all the patterns through the rest of the network; 6) Backpropagate the loss only until the rehearsal layer.

The specific design they utilized with was AR1\*, AR1\*free and LwF CL approaches over a MobileNet-v1 and MobileNet-v2 [21]–[24]. Meanwhile, they opted for simplicity and the trivial rehearsal approach summarized in Algorithm 1 is used for memory management.

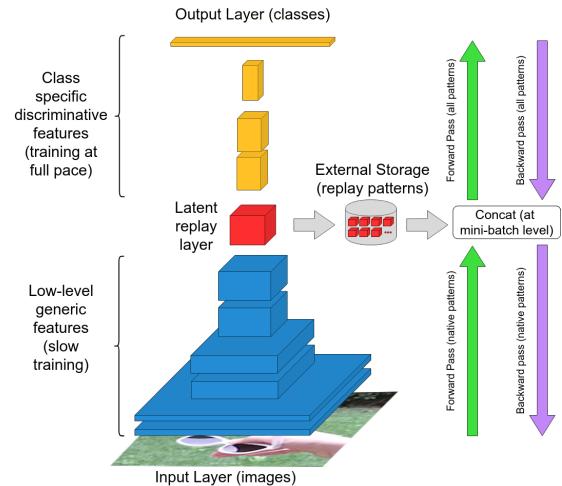


Fig. 4: Architectural diagram of latent rehearsal in Unibo Team.

The full version of this proposed lifelong learning method can be found [here](#) with an Android App demo for continual object recognition at the edge demo on this [YouTube link](#) [25].

### C. Guinness Team

The core backend of the approach was the learning without forgetting (LwF) [26]. Figure 5 illustrates its training strategy. They deployed a pretrained MobileNet-v2 [21], in which the weights up to the bottleneck are retained as  $\theta_p$  ( $\theta_p$  here was fine tuned during training) and they trained the bottleneck weights from scratch. Based on LwF, they retained

TABLE III: IROS 2019 Lifelong Robotic Vision Challenge final results.

Teams	Final Acc. (%)	Model Size (MB)	Inference time (s)	Replay Size (#sample)	Bonus-set Acc. (%)
HIK\_ILG	96.86	16.30	25.42	0	<b>21.86</b>
Unibo	97.68	<b>5.900</b>	<b>22.41</b>	1,500	8.500
Guiness	72.90	9.400	346.0	0	10.96
Neverforget	92.93	342.9	467.1	0	1.520
SDU\_BFA\_PKU	<b>99.56</b>	171.4	2,444	28,500	19.54
Vidit98	96.16	9.400	112.2	1,300	1.390
HYDRA-DI-ETRI	10.42	13.40	1,323	21,312	7.100
NTU\_LL	93.56	467.1	4,213	0	2.100

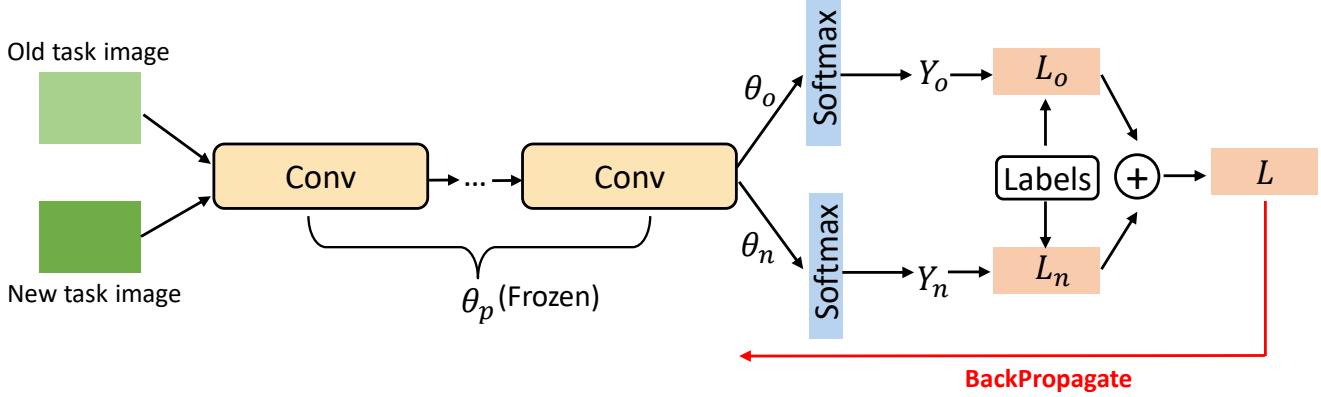


Fig. 5: LwF training strategy proposed by Guinness Team.

**Algorithm 1** Pseudo-code explaining how the external memory  $M$  is populated across the training batches.

```

Require:  $M = \emptyset$ 
Require:  $M_{size}$  = number of patterns to be stored in  $M$ 
For each training batch  $B_i$  do
    train the model on shuffled  $B_i \cup M$ 
     $h = M_{size}/i$ 
     $R_{add}$  = Random sampling  $h$  patterns from  $B_i$ 
     $R_{replace} = \begin{cases} \text{Sample } h \text{ patterns from } M, & \text{if } i > 1 \\ \emptyset, & \text{Otherwise} \end{cases}$ 
     $M = (M - R_{replace}) \cup R_{add}$ 
end for

```

the  $\theta_{old}$  that is trained by previous tasks to construct the regularization term for training new weights  $\theta_{new}$ . It should be noted that there was no replay of previous task images in this structure and only the updated  $\theta_{new}$  was retained after training. Empirically, they loaded the initial pretrained weights  $\theta_p$  when processing a new task and  $\theta_p$  was going to be fine tuned during the training. Details of training scheme are included in Algorithm 2.

#### D. Neverforget Team

The approach was based on Elastic Weight Consolidation (EWC) [27]. As is shown in the Figure 6, the darker area means a smaller loss or a better solution to the task. First, the parameters of the model are initialized as  $\theta^0$  and finetuned as  $\theta^a$  for Task A. Then, if the model continues to learn Task

**Algorithm 2** Training details

**Inputs:**

Training images  $\mathbf{X}$ , labels  $\mathbf{Y}$  of the new task and the pretrained parameters  $\theta_p$

**Initialize:**

$\mathbf{Y}_o \leftarrow \mathcal{M}_{\hat{\theta}_p, \theta_o}(\mathbf{X})$   
 $\theta_n \leftarrow \text{Xavier-init}(\theta_n)$

Load the pretrained weights  $\theta_p$  to the new model

**Train:**

$\theta_p^*, \theta_n^* \leftarrow \underset{\hat{\theta}_p, \hat{\theta}_n}{\operatorname{argmin}} (\lambda \mathcal{L}_o(\mathbf{Y}, \mathbf{Y}_o) + \mathcal{L}_n(\mathbf{Y}, \mathbf{Y}_n))$   
 $\theta_o \leftarrow \theta_n$

B and finetuned as  $\theta^b$  1, the loss of Task A is getting much larger, and it will suffer from the forgetting problem. Instead, the Fisher Information Matrix is utilized to measure the importance of each parameter. If the parameter of the previous task is important, the parameter adjustment in this direction will be constrained and relatively small, if the parameter of the previous task is less important, there will be more space for parameter adjustment in this direction. Assume the importance (the second derivative of log-like function) of parameter  $\theta_2$  is more than  $\theta_1$ , in Task B, the parameter of the neural network will adjust more in  $\theta_1$  direction. Thus, the model will gain knowledge of Task B while preserving the knowledge of Task A simultaneously. The ResNet-101 [28] was used as the backbone network. The task was sequentially trained on the training set.

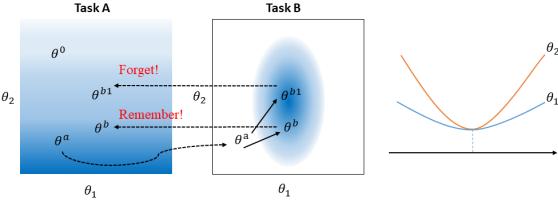


Fig. 6: EWC architecture in Neverforget Team's Solution.

### E. SDU\_BFA\_PKU Team

The approach disentangled this problem with two aspects: background removal problem (See Figure 8) and classification problem.

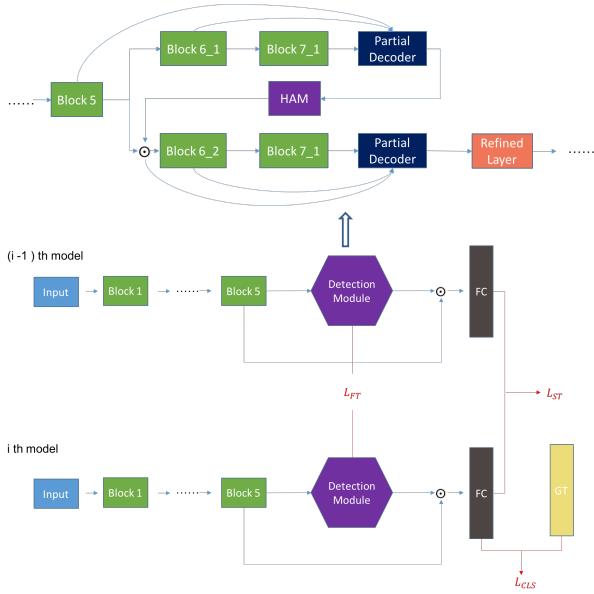


Fig. 7: The architecture proposed by SDU\_BFA\_PKU Team.

First, they utilized saliency detection method to remove the background noise. Cascaded partial decoder framework which contains two branches is applied to get image saliency map. In each branch, they used a fast and effective partial decoder. The first branch generates an initial saliency map which is utilized to refine the features of the second branch. For classification problem with catastrophic forgetting, they utilized knowledge distillation to prevent it. They used an auto-encoder as a teacher translator, and an encoder as student translator, which has same architecture with teacher translator encoder. The model is aim to project saliency maps from teacher network and student network to same space. Specifically, For  $i$ -th task, they regarded  $(i - 1)$ -th model as teacher network, and  $i$ -th model as student network. In order to extract the factor from the teacher network, they trained the teacher translator in an unsupervised way by assigning the reconstruction loss at the beginning of every task training process. Then they utilized student translator to translate student network's saliency map output, computed  $L_1$  loss between teacher network output and student network. In order to save computational and storage size, they used MobileNet-v2 as backbone model [21].



Fig. 8: A background removal demo in SDU\_BFA\_PKU Team's solution.

### F. Vidi98 Team

This approach sampled validation data from the buffer and use it as replay data. It intelligently creates the replay memory for a task. Here suppose a network is trained on a task  $t_n$  and it learns some feature representation of the images in the task, when trained on the task  $t_{n+1}$  it learns the feature representation for images in task  $t_{n+1}$ , but as the distribution of data in task  $t_{n+1}$  is different, accuracy drops for images in task  $t_n$ . The replay memory was an efficient representation of previous tasks data whose information was lost. The replay data was sampled from the validation of all the previous tasks. The network on task  $t_n$  is trained and the accuracy of batches of validation data is saved. Next, when trained on task  $t_i$  ( $i > n$ ), the accuracy of same batches of validation data of task  $t_n$  is calculated. Then they stored the top  $k$  batches from validation data of task  $t_n$  whose accuracy has dropped the most. This is done for all the tasks  $t_0$  to  $t_{i-1}$ . Training for task  $t_{i+1}$  they combined the replay data and training data to train for the particular task. The algorithm is shown in Algorithm 3. The backbone model they used is MobileNet-v2 [21]. [Code](#) is made available.

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#### Algorithm 3 Intelligent resampling method

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**Results:** Replay\_Data

**Initialization:**

```

 $F_i, val\_data_i, t_n, acc[], best\_acc[], topk$ 
While data in  $val\_data_i$  do:
    prec = Accuracy( $F_i(data)$ )
    Add prec to  $acc[]$ 
end
if  $i == n$  then:
    Add  $acc$  to  $best\_acc$ 
else
    diff =  $best\_acc - acc$ 
    sort_diff = sort(diff)
    Add  $topk$  elements corresponding to  $sort\_diff$  from  $val\_data_i$  to Replay_Data;
```

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### G. HYDRA-DI-ETRI Team

The team proposed a selective feature learning method to eliminate irrelevant objects in target images. A Single Shot multibox Detection (SSD) algorithm selected desired objects [29]. The SSD algorithm alleviated performance degradation by noisy objects. Then SSD weights were trained

with annotated images in task 1, and the refined dataset was fed into a traditional MobileNet [24].

The team also analyzed OpenLORIS-Object dataset to design object recognition software (See Figure 10), and find that target objects in the dataset coexist with unlabeled objects. The region of interest analysis is illustrated in Figure 9. Therefore, they proposed a selective feature learning method by eliminating irrelevant features in training dataset. The selective learning procedure is as follows: 1) extracting target objects from training dataset by an object detection algorithm, 2) feeding the refined dataset into a deep neural network to predict labels. In their software, they applied to a SSD as the object detection algorithm due to convenience of flexible feature network design and proper detection performances.

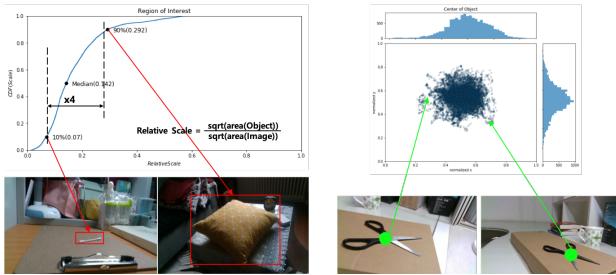


Fig. 9: Region of interest analysis in HYDRA-DI-ETRI Team's solution.

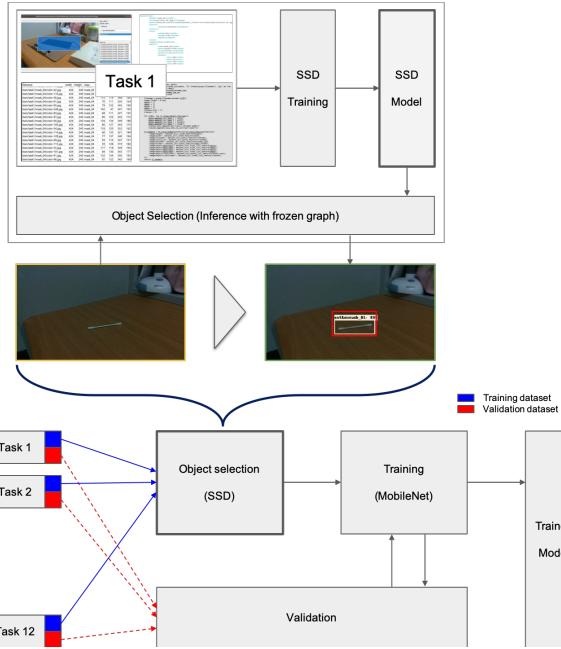


Fig. 10: Software architecture for selective feature learning in HYDRA-DI-ETRI Team's solution.

#### H. NTULL Team

The team utilized a combination of Synaptic Intelligence (SI) based regularization method and data augmentation [9] (See Figure 11). The augmentation strategies they applied

were Color Jitter and Blur. ResNet-18 was used for backbone model [28].

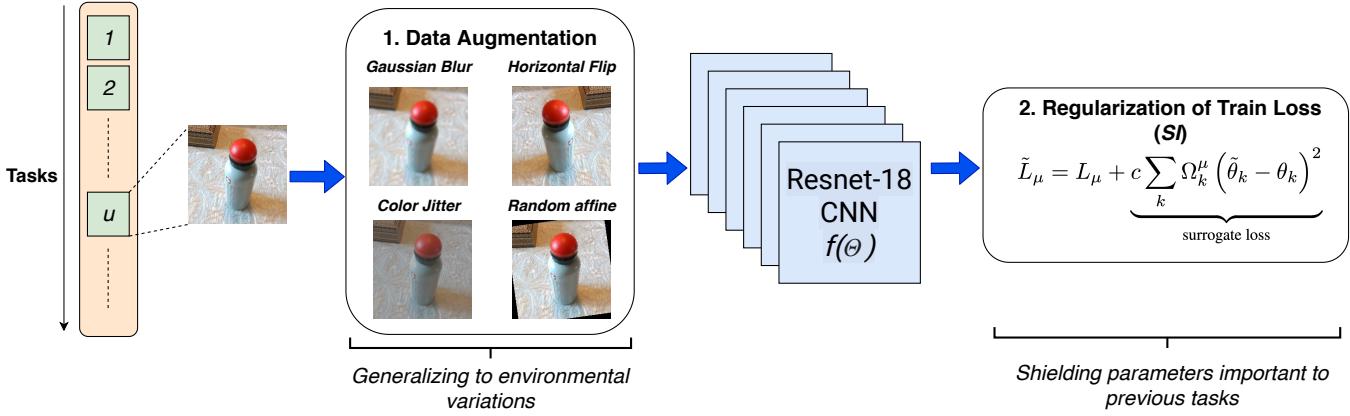


Fig. 11: Solution architecture proposed by NTU\_LL Team.

#### IV. FINALISTS INFORMATION

##### HIK.ILG Team

**Title:** *Dynamic Neural Network for Incremental Learning*

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**Affiliation:** <sup>1</sup>Hikvision Research Institute, Hangzhou, China.

##### Unibo Team

**Title:** *Efficient Continual Learning with Latent Rehearsal*

**Members:** Gabriele Graffieti<sup>1</sup>, Lorenzo Pellegrini<sup>1</sup>, Vincenzo Lomonaco<sup>1</sup> and Davide Maltoni<sup>1</sup>

**Affiliation:** <sup>1</sup>University of Bologna, Bologna, Italy.

##### Guinness Team

**Title:** *Learning Without Forgetting Approaches for Lifelong Robotic Vision*

**Members:** Zhengwei Wang<sup>1</sup>, Eoin Brophy<sup>2</sup> and Tomás E. Ward<sup>2</sup>

**Affiliation:** <sup>1</sup>Zhengwei Wang is with V-SENSE, School of Computer Science and Statistics, Trinity College Dublin, Dublin, Ireland; <sup>2</sup>Eoin Brophy and Tomás E. Ward are with the Insight Centre for Data Analytics, School of Computing, Dublin City University, Dublin, Ireland.

##### Neverforget Team

**Title:** *A Small Step to Remember: Study of Single Model VS Dynamic Model*

**Members:** Liguang Zhou<sup>1,2</sup>

**Affiliation:** <sup>1</sup>The Chinese University of Hong Kong (Shenzhen), Shenzhen, China, <sup>2</sup>Shenzhen Institute of Artificial Intelligence and Robotics for Society, China.

##### SDU\_BFA\_PKU Team

**Title:** *SDKD: Saliency Detection with Knowledge Distillation*

**Members:** Lin Yang<sup>1,2,3</sup>

**Affiliation:** <sup>1</sup>Peking University, Beijing, China, <sup>2</sup>Shandong University, Qingdao, China, <sup>3</sup>Beijing Film Academy, Beijing, China.

##### Vidit98 Team

**Title:** *Intelligent Replay Sampling for Lifelong Object Recognition*

**Members:** Vidit Goel<sup>1</sup>, Debdoot Sheet<sup>1</sup> and Somesh Kumar<sup>1</sup>

**Affiliation:** <sup>1</sup>Indian Institute of Technology, Kharagpur, India.

##### HYDRA-DI-ETRI Team

**Title:** *Selective Feature Learning with Filtering Out Noisy Objects in Background Images*

**Members:** Soonyong Song<sup>1</sup>, Heechul Bae<sup>1</sup>, Hyonyoung Han<sup>1</sup> and Youngsung Son<sup>1</sup>

**Affiliation:** <sup>1</sup>Electronics and Telecommunications Research Institute (ETRI), Korea.

##### NTU\_LL Team

**Title:** *Lifelong Learning with Regularization and Data Augmentation*

**Members:** Duvindu Piyasena<sup>1</sup>, Sathurasan Kanagarajah<sup>1</sup>, Siew-Kei Lam<sup>1</sup> and Meiqing Wu<sup>1</sup>

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#### ACKNOWLEDGMENT

The work was partially supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. CityU 11215618). The authors would like to thank Hong Pong Ho from Intel RealSense Team for the technical support of RealSense cameras for recording the high-quality RGB-D data sequences.

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