Camouflaged Object Detection

GNR 638 Course Project

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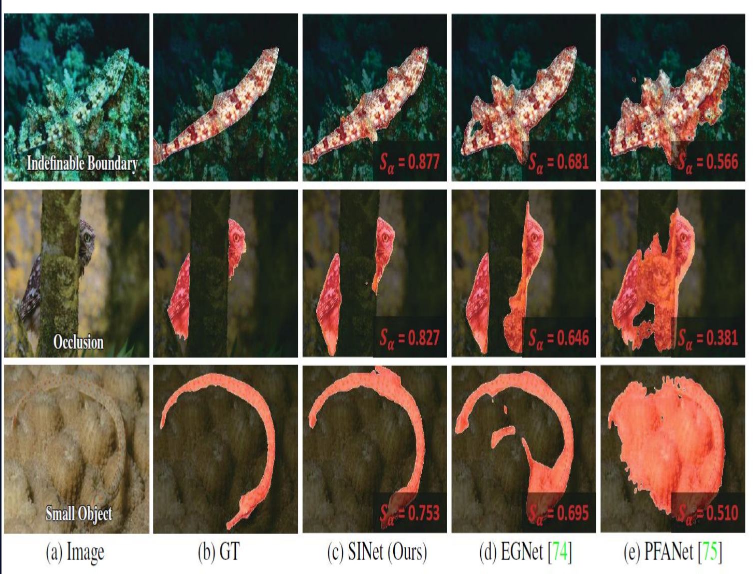

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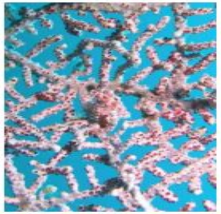



Problem Statement:
Camouflaged Object Detection

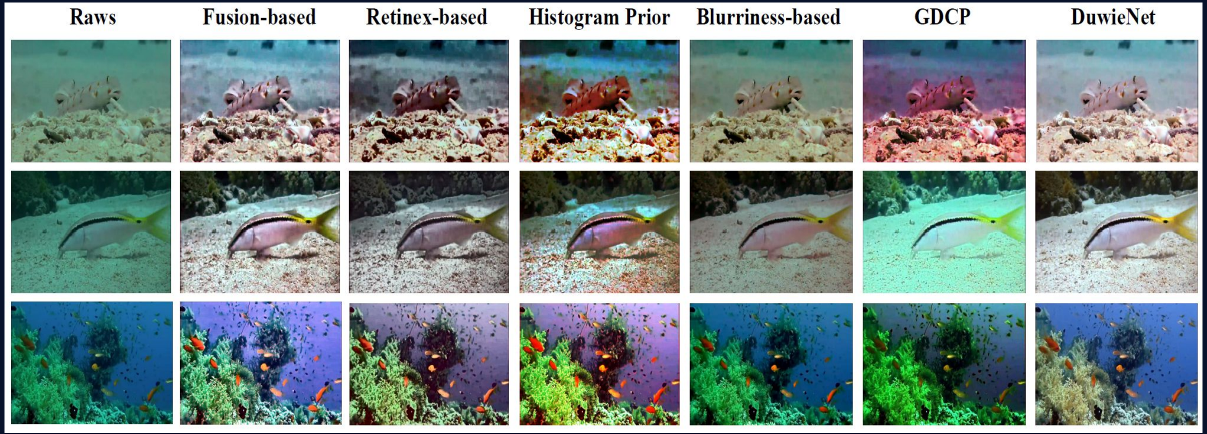
To precisely search and identify camouflaged objects.

To overcome the challenge of object detection despite of being high intrinsic similarities between target object and background.

Background Study

- The oldest recorded studies in camouflaged objects come from papers by Thayer and Cott classifying camouflage into natural (e.g. animals) and artificial (e.g. adulterants, defective products) kinds.
- The most well-known datasets prior to *COD10K* were the unpublished *CHAMELEON* and *CAMO*, however both provided few images of acceptable quality and were sparsely annotated.
- Detection of camouflaged objects was performed at a pixel-level, by assigning each pixel with a confidence probability. The higher the probability, the greater are the chances of the pixel belonging to a camouflaged object.
- The MAE metric, while popular with salient object detection, cannot judge structural similarities, hence the need for a new evaluation metric.

COD10K Dataset



- Contains 10K images covering 78 camouflaged object categories such as aquatic, flying, amphibians, terrestrial etc.
    - 6K training images
    - 4K testing images

COD10K Dataset

- All the camouflaged images are hierarchically annotated (taxonomic system) as:
  - Category
  - Bounding box
  - Attribute
  - Object/Instance
- Facilitates many vision tasks, such as localization, object proposal, semantic edge detection, task transfer learning etc.
- Each camouflaged image is assigned challenging attributes and matting level which provides deeper insights into the algorithm

Major Contributions by the Paper

- Carefully assembled the COD10K dataset:
  - 10K images (78 categories)
- Used two existing datasets + collected COD images, rigorous evaluation of 12 state-of-the-art baselines making largest COD study ever
- Proposed SINet framework which outperformed all existing methods
  - Provided potential solution to the highly challenging problem of camouflaged object detection

The Project Pipeline

Data Loading
+
Pre-processing

The Architecture:
SINet
Framework

Training +
Testing
Results

Data Loading + Data Pre-processing

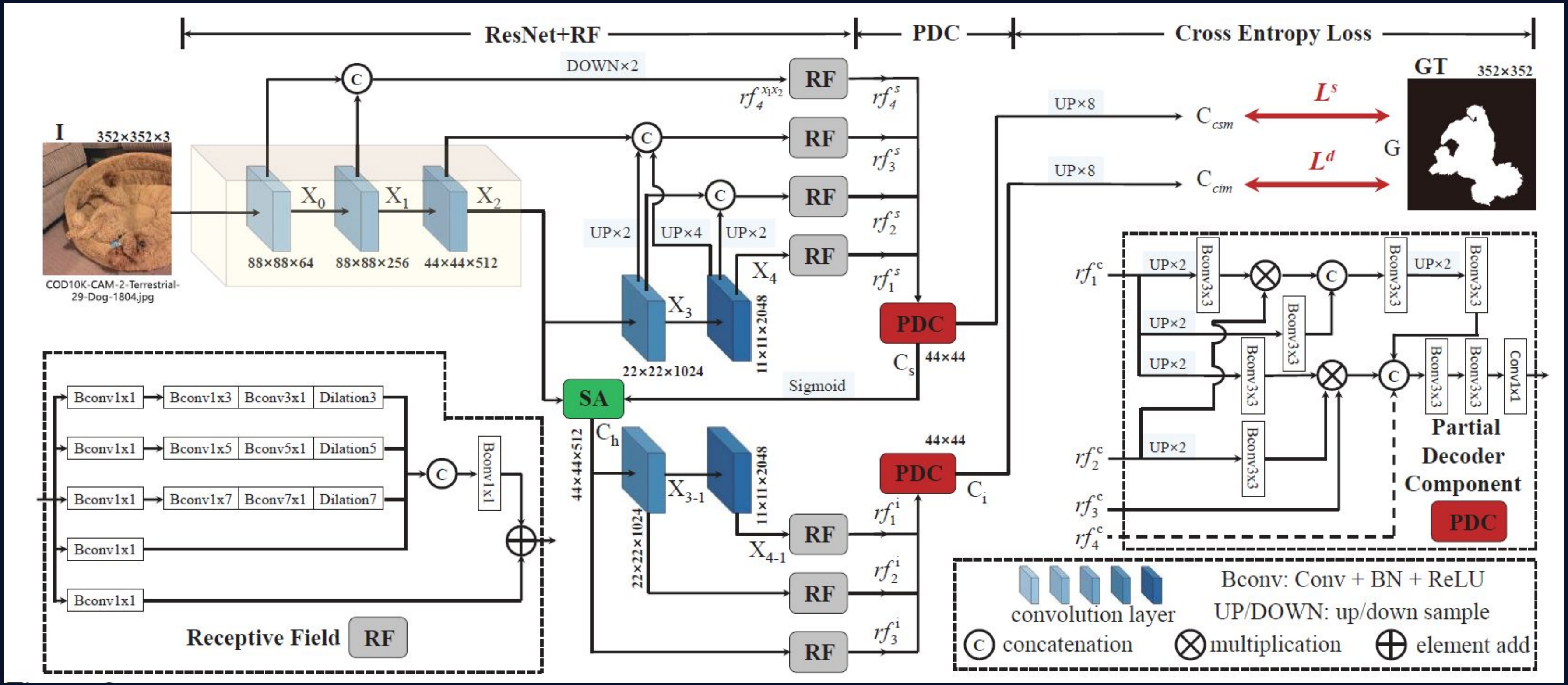
- A PyTorch DataLoader is defined to collate the training as well as test datasets into separate iterable *dataloader* objects.
- The images are then resized, converted to a PyTorch tensor and normalized.
- Images are further processed into one of two forms:
  - Colour image to 3-channel RGB image
  - Colour image to single channel grayscale image ("L" mode)

The Architecture

- SINet framework
  - Search Module(search of camouflaged objects)
  - Identification Module(precise detection)

    (Inspired by hunting!)
- Two Components
  - Receptive Field Module
  - Partial Decoder Component

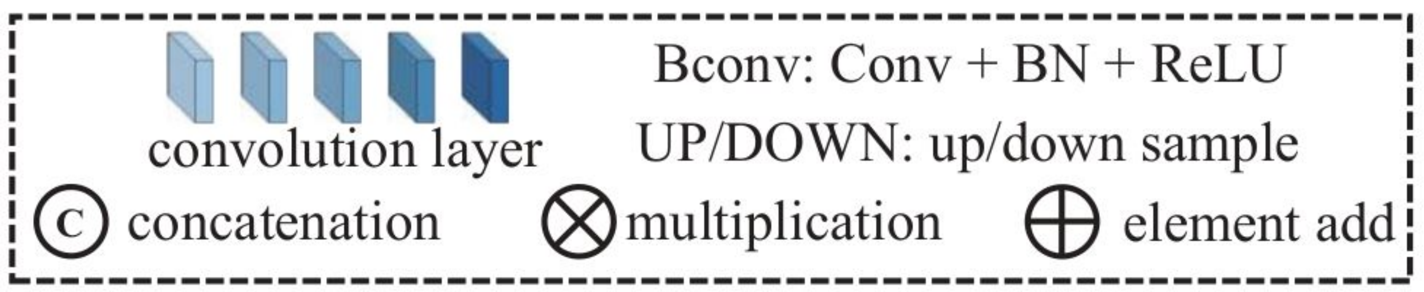
Switcher: Search Attention Module



SINet Architecture

Define: The Bconv Operation

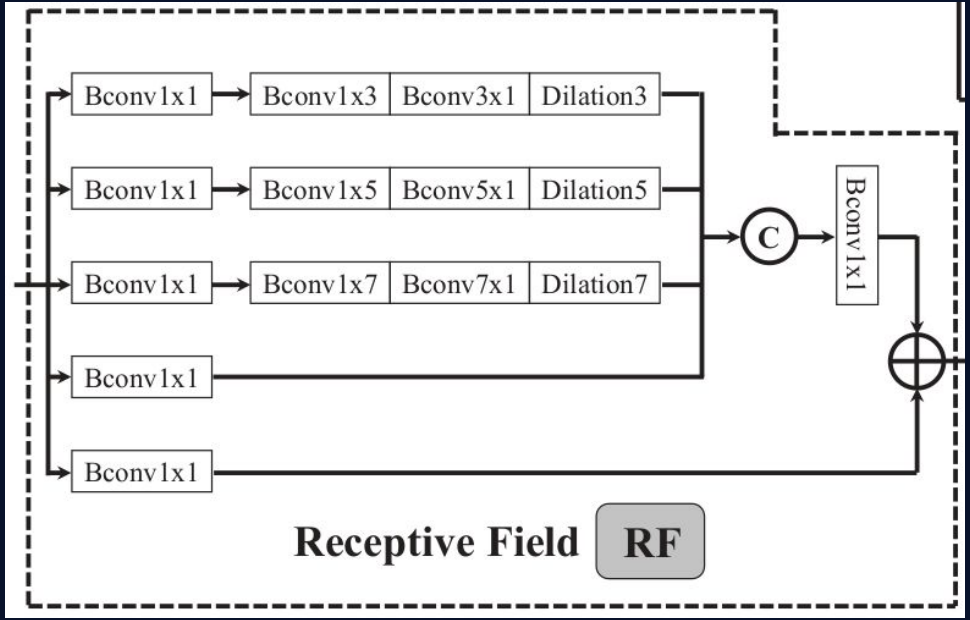
- BConv:
  - Convolutional layer
  - Batchnorm layer
  - ReLU activation



The Search Module

- Uses **Receptive Field component** to incorporate more discriminative feature representations during the searching stage
- For input image, set of features extracted from **ResNet50**:
  - X0, X1 : Low level features
  - X2 : Middle level features
  - X3, X4 : High level features
- Extracted features concatenated, upsampled, downsampled to form dense net
- Set of enhanced features are obtained after feeding into RF component for learning robust cues

Receptive Field Component

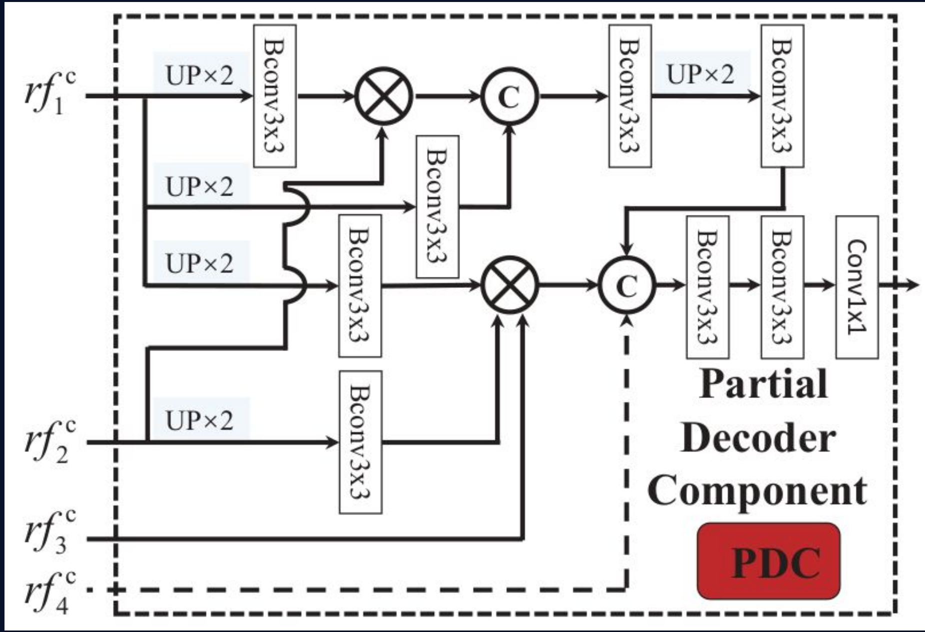


- Includes 5 branches: b_k,(k=1,...,5)
- In each branch:
  - First conv. layer has dimensions as 1x1 to reduce the channel size to 32
  - Followed by (2k-1)x(2k-1) Bconv layer & dilation = 2k-1
- b_1, b_2, b_3, b_4: concatenated
- b_5 added and model fed to ReLU

The Identification Module

- Uses **<u>Partial Decoder component(PDC)</u>** to precisely detect candidate features obtained from previous search module
- PDC:
  - Integrates 4 levels of features from Search Module
  - Obtains coarse camouflaged map C_s
- Switcher **<u>Search Attention Module</u>** Introduced which:
  - Enhances middle level features X2
  - Effectively eliminates interference from irrelevant features

Partial Decoder Component(PDC)



- New features generated from existing features coming from search and identification stages
- Element-wise multiplication adopted to decrease the gap between adjacent features

Partial Decoder Component(PDC)

- **The features coming from search and identification stages are given as:** $\{rf_k^c, k \in [m, \ldots, M], c \in [s, i]\}$
- **New features generated from PDC:** $\{rf_k^{c1}\}$
- **Shallow features:** $rf_M^{c1} = rf_M^{c2}$ when $k = M$.
- **Deeper features:** $rf_k^{c1}, k < M$, we update it as rf_k^{c2}:

$$rf_k^{c2} = rf_k^{c1} \otimes \Pi_{j=k+1}^{M} Bconv(UP(f_j^{c1})).$$

where $k \in [m, \ldots, M-1]$.

Search Attention Module

- Coarse camouflaged map C_s(from search module): $C_s = PD_s(rf_1^s, rf_2^s, rf_3^s, rf_4^s)$, where $\{rf_k^s = rf_k, k = 1,2,3,4\}$
- SA module enhances features as: $C_h = f_{max}(g(\mathcal{X}_2, \sigma, \lambda), C_s)$,
  - g(.) : SA function(which is a gaussian filter with kernel_size = 4 and dev.=32)
  - f_max : maximum function that highlights initial camouflaged regions
- To obtain high level features, PDC is aggregated to another three levels of features, enhanced with RF to obtain final camouflaged map C_i:

$C_i = PD_i(rf_1^i, rf_2^i, rf_3^i)$, where $\{rf_k^i = rf_k, k = 1,2,3\}$

Loss Function

C_{csm}

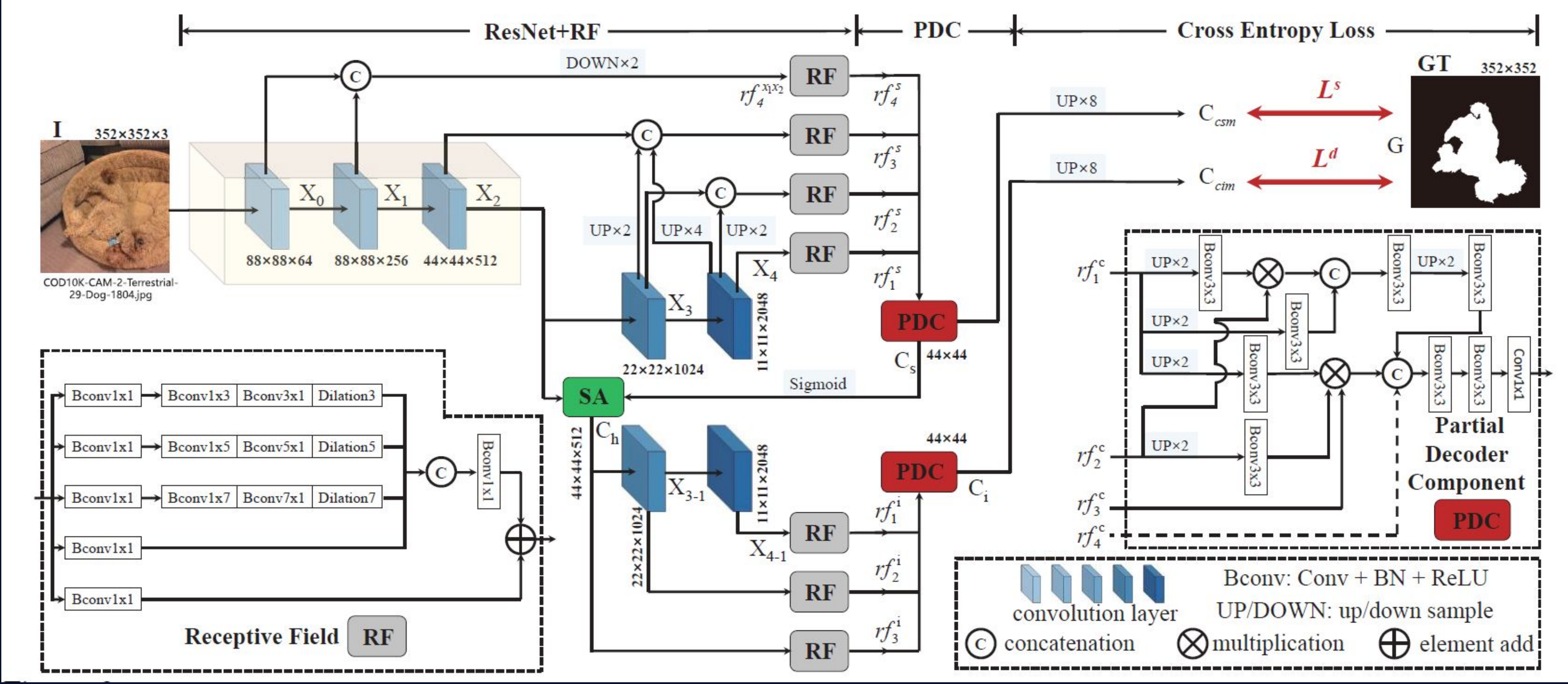
Camouflaged map obtained after upsampling C_s to a resolution of 352x352

C_{cim}

Camouflaged map obtained after upsampling C_i to a resolution of 352x352

$$L = L_{CE}^{\mathrm{s}}(C_{csm}, G) + L_{CE}^{\mathrm{i}}(C_{cim}, G).$$

Summarizing SINet Framework



Training and Testing Results:

Training

- Trained models (base and modified) for 20-40 epochs
- Achieved MAE on base model of about 0.02 on the train set in only 20 epochs (computational constraints)
- Achieved MAE on modified model (modified for speed) of about 0.027 on the train set in 40 epochs

Test

- Achieved a MAE of 0.091 averaged on test set using base model in only 20 epochs
- Achieved a MAE of 0.094 averaged on test set using modified model in 40 epochs

Modifications

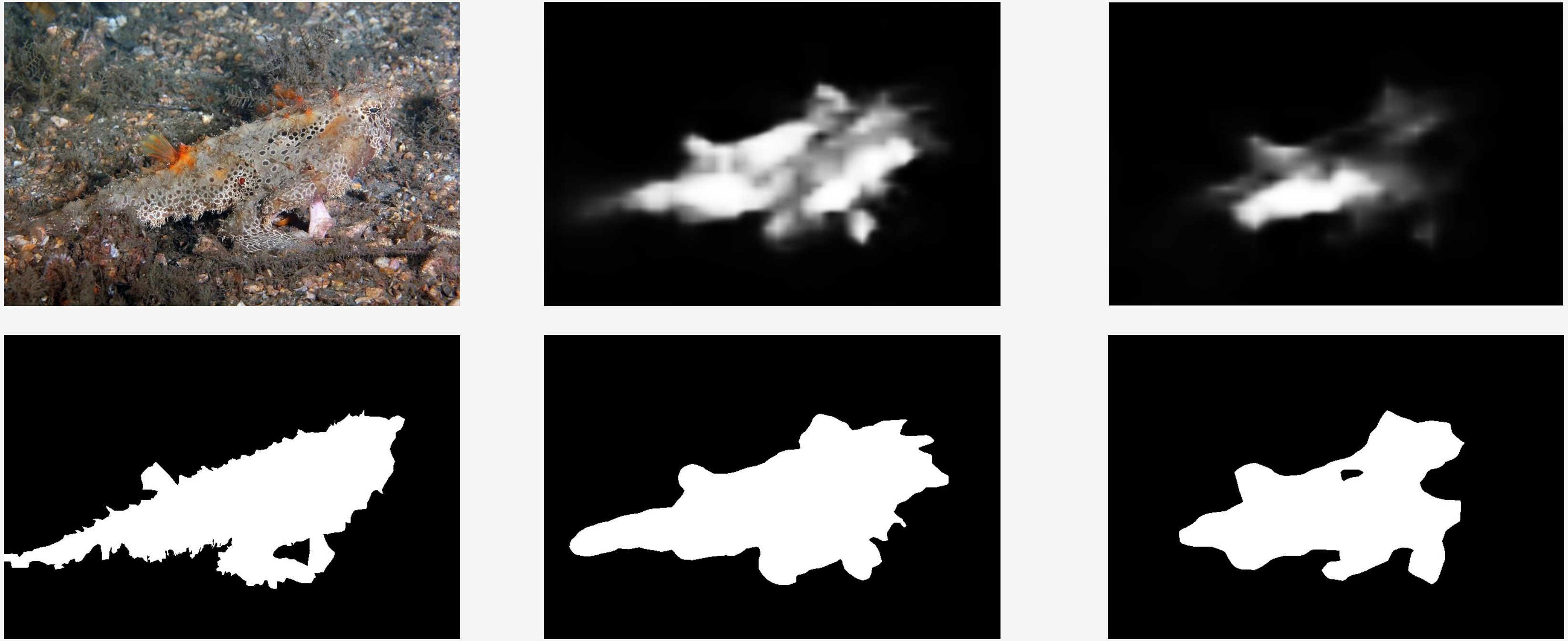
Proposed modifications

- Decrease resolution of input images to speeden up the training process while still achieving our goal of detecting and localizing the camouflaged object
- Doubling the number of channels to 64 in the RF module (lead to exploding gradients)
- Increasing the depth of the network (hurdle of computational resources)

Modification 1 showed promising results

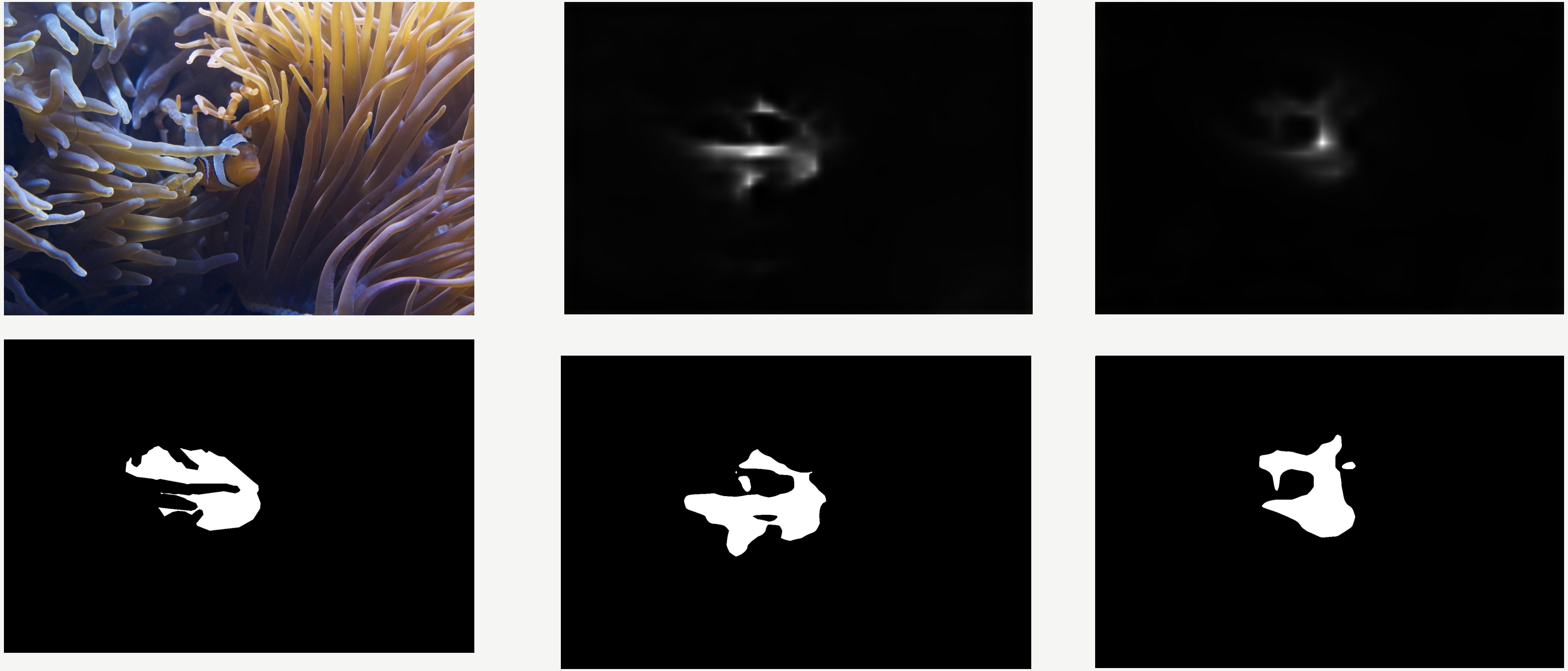
Results

Camouflaged testing img | base model | modified



Results

Camouflaged testing img | base model | modified



Results

Camouflaged testing img

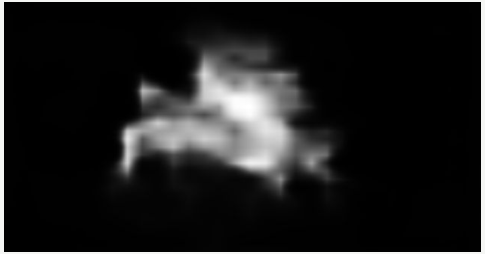
base model

modified

Results

Camouflaged testing img

base model



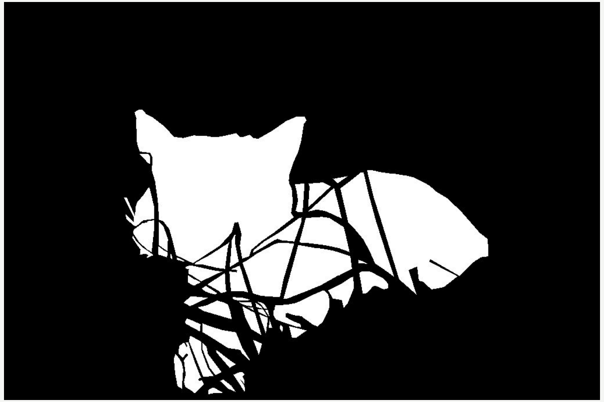
modified

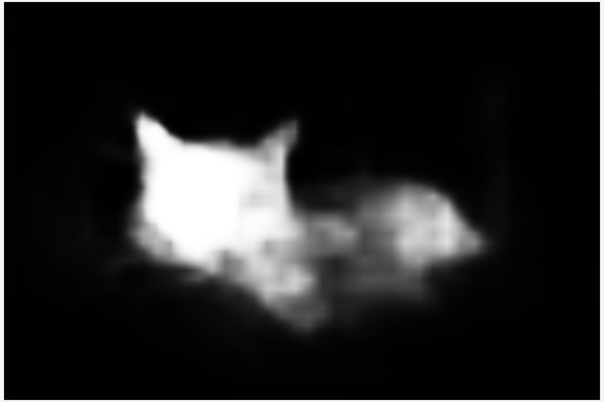
Results

Camouflaged testing img

ground truth

base model



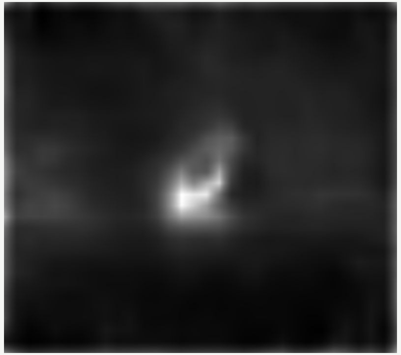


Results

Non -Camouflaged test img

base model

modified



References:

- Link to the original paper: Camouflaged Object Detection(CVPR 2020)
- Dataset: COD10K
- Original Github Repository: SINet
- ResNet50: ResNet50

Contributions

- Shubham Lohiya:
    - Dataset acquirement + extraction
    - Training base model
    - Training modified models
    - Evaluation of models on test sets
    - Analysis of evaluation data
    - Post-processing of results

Contributions

- Aditya Iyengar:
  - Shortlisting the paper and finalizing the problem statement
  - Background study by reviewing similar papers
  - Creating the data loader for training and testing data
  - Comparison and implementation of various techniques for preprocessing
  - Training with several loss functions to identify the best fit
  - Performed systematic documentation for the entire code

Contributions

- Sharvaree Sinkar:
  - Created modified ResNet50 backbone code
  - Wrote code for SINet framework from scratch
  - Analysis of Search and Identification Modules
  - Study of Partial Decoder Component and Receptive Field
  - Examined relations between PDC and RF
  - Entire Analysis of SINet architecture
  - Made Presentation slides