# Improved TC-USOD Model for Underwater Saliency Detection

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# Introduction

**What is Underwater Saliency Detection?**

- Saliency detection highlights the areas in an image that catch the eye the most

# Problem Statement

**Problem Statement:**

- Underwater object detection suffers from challenges such as light scattering, absorption, and color distortions.

# Dataset Overview

**USOD10K: Underwater Salient Object Detection Dataset**

- **Size:** 10,255 annotated underwater images.
- **Diversity:**
  - 70 object classes, 12 scenarios.
  - Includes varying object sizes: small, medium, large.
- **Annotations:**
  - Salient object boundaries.
  - Depth maps for RGB-D integration.

# The best model in USOD10K (TC-USOD)

**TC-USOD: A Model for Underwater Object Detection**

- **Transformer Encoder:** Captures global features from images.
- **Convolutional Decoder:** Creates saliency maps to highlight objects.

**Input and Output:**

- **Input:** Underwater images (with or without depth maps).
- **Output:** Maps showing important objects.

# Observations from Outputs of the TC-USOD model

**problems we observed:**

- we observed that the outputs have more dominance of red and blue color's
- blurred and unclear regions these may affect the detection accuracy

**Impact on Outputs:**

- Incorrect detection of salient objects due to color and clarity issues.

# solving color dominance issues

**problem:**

- dominance of red and blue colors in outputs reduced the detection accuracy and affected the saliency map quality.

**to solve this, we applied preprocessing techniques:**

- used **color balance and fusion:**
  - restored natural color balance by applying the *gray world algorithm*.
  - improved contrast and brightness using **gamma correction**.
- enhanced visibility by **sharpening image features**.

**outcome:**

- saliency maps with balanced colors, better contrast, and improved visual clarity.

# enhancing clarity in detection

**problem:**

- blurred and unclear regions in the outputs caused misinterpretation of object boundaries.

**to solve this, we introduced the depth auxiliary module (dam):**

- implemented **cross-modality fusion (cmf):**
  - enhanced depth maps using spatial and channel attention mechanisms.
  - combined rgb and depth features to refine object boundaries.

**outcome:**

- saliency maps with sharper object boundaries and improved clarity.

# improving feature integration

**problem:**

- lack of integration between low-level and high-level features resulted in missed details in the saliency maps.

**to solve this, we applied multi-level feature fusion:**

- combined **low-level fine-grained features** with **high-level global features**

**outcome:**

- improved saliency maps with detailed and holistic object representations.

# training with a hybrid loss function

**problem:**

- conventional loss functions could not balance saliency accuracy and boundary precision.

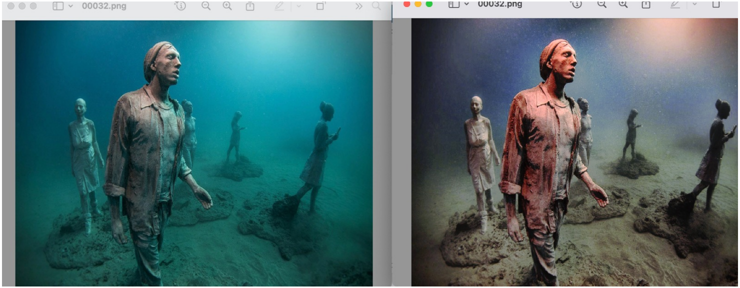
**to solve this, we designed a hybrid loss function:**

- combined **binary cross-entropy (bce)**, **iou**, **dice**, and **ssim** losses.
- ensured the model focused on both **saliency detection** and **boundary accuracy**.

**outcome:**

- generated saliency maps with accurate boundaries and high detection precision.

# before and after preprocessing results




**comparison: before (left) and after (right)**

# visual comparison: saliency maps

**baseline vs. improved tc-usod:**

- improved tc-usod demonstrates sharper boundaries and better detection of salient regions.
- particularly effective in turbid and low-contrast underwater conditions.

# effectiveness of hybrid architecture

**key observations:**

- pure convolutional models achieved:
  - s-measure: 0.8222
  - mae: 0.0628
- hybrid models with depth auxiliary module (dam) and cross-modality fusion (cmf):
  - s-measure: 0.9215
  - mae: 0.0201
- new tc-usod:
  - s-measure: 0.9116
  - mae: 0.0238

# effectiveness of hybrid loss

**key improvements:**

- loss functions tested:
  - **bce only:** s-measure: 0.9126, mae: 0.0224
  - **bce + dice + ssim:** s-measure: 0.9161, mae: 0.0299
  - **bce + iou + dice + ssim (hybrid):** s-measure: 0.9215, mae: 0.0201
- hybrid loss demonstrated better boundary precision and overall saliency detection performance.

# quantitative comparison of results

**performance metrics**

- **s-measure (sm):**
  - baseline tc-usod: 0.9021
  - improved tc-usod: 0.8946
- **mae:**
  - baseline tc-usod: 0.0228
  - improved tc-usod: 0.0238
- **e-measure (eme):**
  - baseline tc-usod: 0.9568
  - improved tc-usod: 0.9516
- **ap and auc:**
  - baseline tc-usod auc: 0.9607, ap: 0.8953
  - improved tc-usod auc: 0.9638, ap: 0.8963

# conclusion

**improved tc-usod:**

- enables more reliable detection of underwater salient objects.
- enhances boundary clarity for complex underwater environments.
- scalable and adaptable for related underwater imaging tasks.

# Conclusion

**Key Takeaways:**

- Improved TC-USOD successfully addresses underwater saliency detection challenges.
- Outperforms existing methods with DAM, multi-level fusion, and hybrid loss.
- Sets a new benchmark for underwater saliency detection tasks.

# future improvements

**for future work:**

- **depth map estimation:**
  - develop more robust methods for accurate depth estimation in underwater environments.
  - address challenges caused by overlapping objects and varying viewpoints.
- **co-saliency detection:**
  - extend the model for detecting co-occurring salient objects across multiple images.
  - analyze group behavior or patterns in underwater scenes.

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# Thank You!