EE604 PROJECT

MULTIPLE CAMOUFLAGED OBJECT DETECTION

GROUP 22

CONTENT

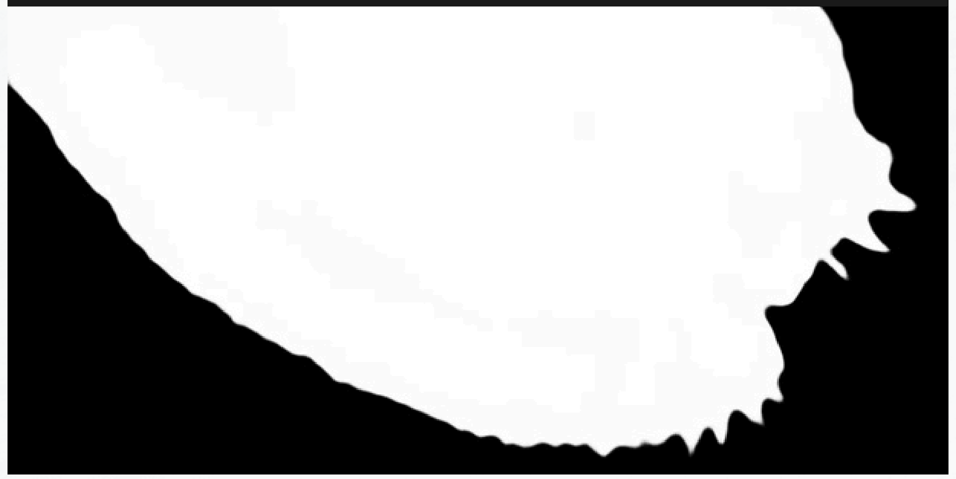
PROBLEM STATEMENT

Input

Input consists of high-resolution images containing camouflaged objects that blend seamlessly into surroundings, challenging traditional segmentation methods

Binary mask that highlights camouflaged objects in the image.

Output



CONSTRAINTS FOR CAMOUFLAGED OBJECT DETECTION

Visual Similarity with Background

Camouflaged objects often share colors, textures, and patterns with their surroundings, making them hard to distinguish from the background using standard segmentation techniques

Subtle and Irregular Boundaries

The boundaries of camouflaged objects are often not well-defined, with edges that are subtle or blend seamlessly into the background, complicating accurate boundary detection

Limited Data and Diverse Scenarios

There is a scarcity of high-quality labeled datasets for camouflaged object detection, and camouflage scenarios can vary greatly, requiring models to generalize across a wide range of visual conditions.

LITERATURE REVIEW

General Segmentation Models

Standard segmentation models struggle with camouflaged object detection (COD) due to their lack of attention to subtle details in camouflaged objects

BiRefNet

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Architecture which enhances COD by combining:

- **Localization Module** (LM): Utilizes a vision transformer to capture multi-scale, coarse-to-fine features for identifying potential regions with camouflaged objects.
- **Reconstruction Module** (RM): - Leverages high-resolution inward and outward references, preserving spatial details and focusing on gradient-based edges for precise segmentation.

SINet-V2

Designed specifically for COD, using combined datasets (COD10K and CAMO) to improve generalization

PROPOSED METHOD

Model selection

BiRefNet (trained on COD10K dataset for 125 epochs)

- This specific BiRefNet model achieved higher performance metrics on camouflaged wildlife objects compared to a general-purpose BiRefNet.
- Focused design with **higher Average IoU** and **F-measure** values, making it well-suited for detecting fine details and subtle boundaries in camouflaged objects.

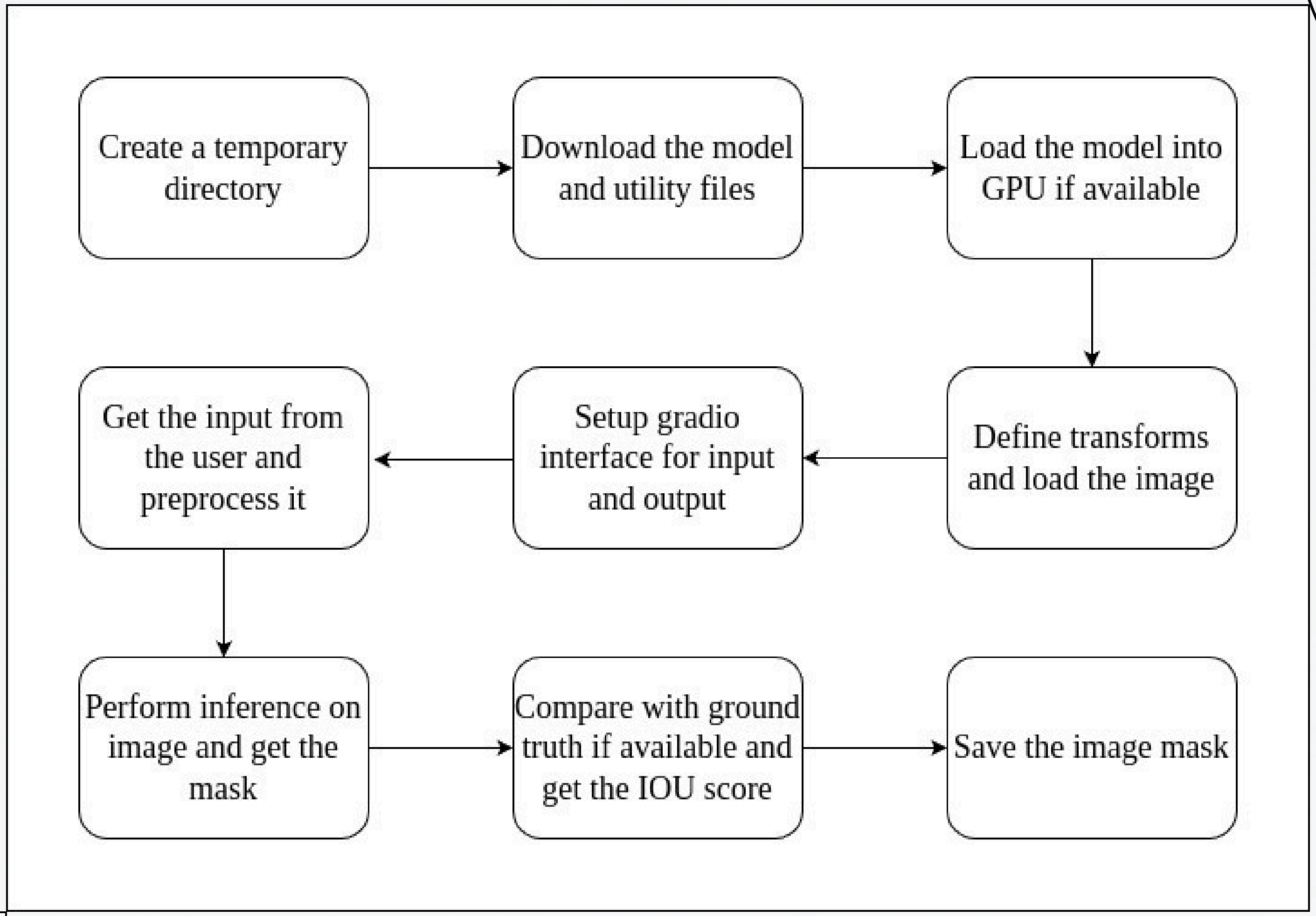
Dataset selection

COD10K Dataset

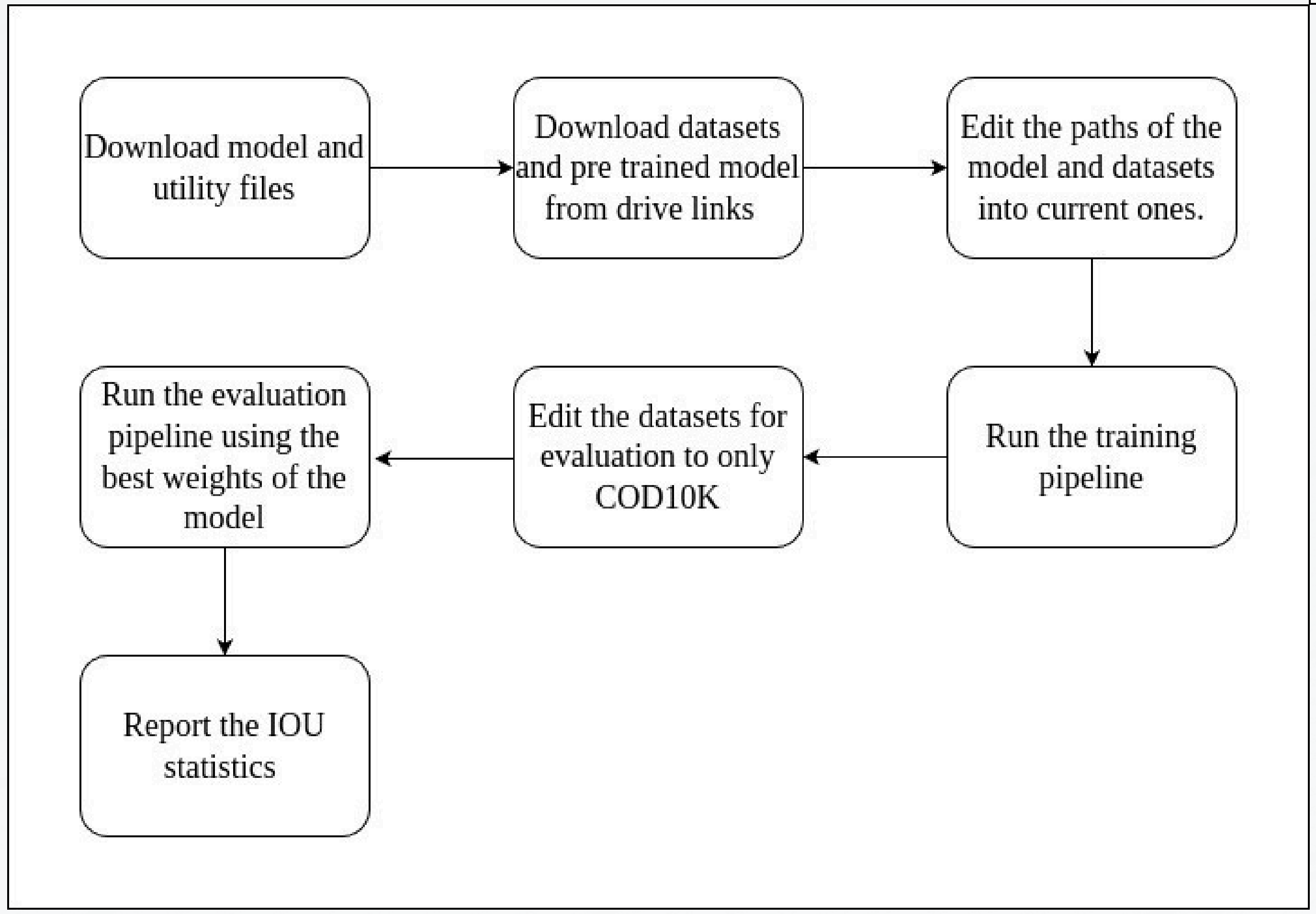
- COD10K includes **10,000 images** covering a wide range of natural and artificial backgrounds, ideal for training on various camouflage patterns.
- Provides **high-resolution images**, crucial for detecting the fine details and subtle edges necessary in camouflaged object detection (COD).

PROPOSED METHOD

App Architecture



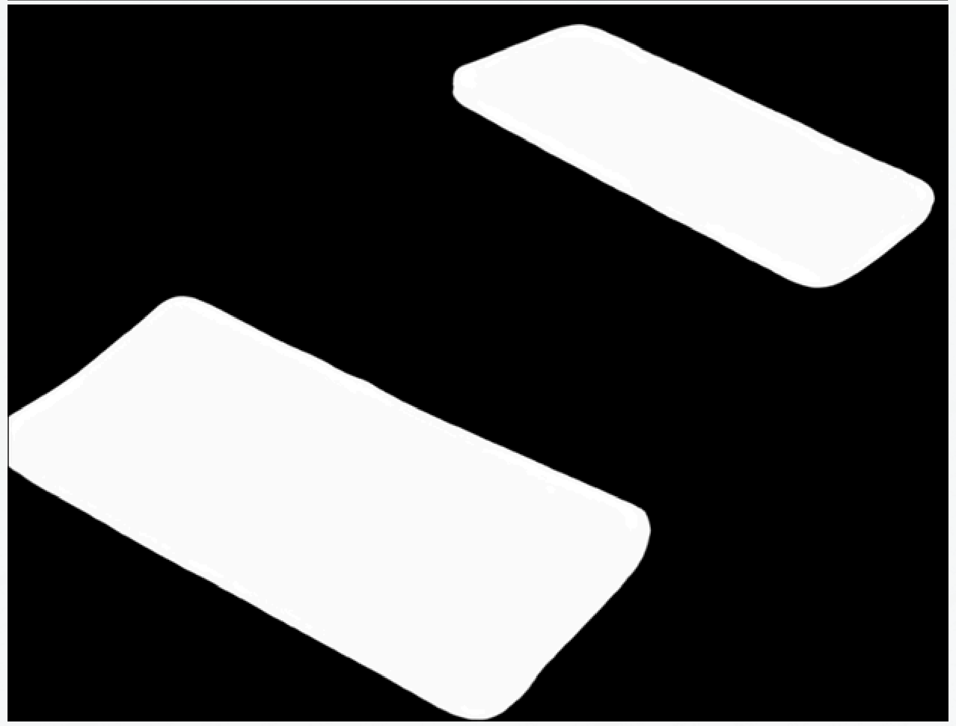
Fine-tuning Pipeline



EXPERIMENTS

Input

Output



Input

Output

EXPERIMENTS

TABLE I

Comparison of IoU Scores between Model A and Model B

Metric	Model A	Model B
Average IoU	0.7992	0.6236
Minimum IoU	0.0000	0.0000
Maximum IoU	0.9895	0.9818
Standard Deviation of IoU	0.1831	0.2581

TABLE III

IoU Metrics for Fine-Tuned Model C

Metric	Model C
Average IoU	0.6236
Minimum IoU	0.0000
Maximum IoU	0.9818
Standard Deviation of IoU	0.2581

TABLE II

Performance Metrics for Model A on COD10K dataset

Metric	Score
Max F-measure (maxFm)	0.454
Weighted F-measure (wFmeasure)	0.443
Mean Absolute Error (MAE)	0.078
Structure Measure (Smeasure)	0.885
Mean Enhanced Measure (meanEm)	0.908
Hausdorff Contour Error (HCE)	67
Max Enhanced Measure (maxEm)	0.912
Mean F-measure (meanFm)	0.450
Adaptive Enhanced Measure (adpEm)	0.795
Adaptive F-measure (adpFm)	0.445
Max Boundary IoU (maxBIoU)	0.376
Mean Boundary IoU (meanBIoU)	0.369

Model A: BirefNet, trained specifically on COD10K dataset
Model B: BirefNet, trained for general use
Model C: Finetuned SINet-V2 model

FUTURE PROSPECTIVES

Since our model performs well on most images but occasionally fails to detect certain camouflaged objects, our future improvement plan includes:

1. Collecting additional, non-overlapping test datasets to ensure diverse and challenging scenarios.
2. Identifying common characteristics in images where the model fails, to gain insights for targeted improvements.
3. Creating precise Ground Truth References through careful annotation of camouflaged objects.
4. Training on a suitable, enhanced dataset to better capture the nuances of camouflaged objects.
5. Re-evaluating the model's performance on these challenging images to assess the impact of these improvements.

REFERENCES

- Github link for SINet-V2 model
- Github link for BiRefNet model
- COD10K dataset
- Dataset for Evaluating finetuned SINet-v2 model
- Dataset used for finetuning SINet v2

THANK YOU