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Article

Enhancing Camouflaged Object Detection with SINet: A New Benchmark in Visual Recognition

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Abstract: The domain of Camouflaged Object Detection (COD) focuses on the intricate task of discerning objects that are visually integrated into their surroundings. The inherent complexity of COD stems from the seamless blending of camouflaged objects with their environment and the indistinct boundaries these objects often possess. To address these challenges, we have meticulously assembled a comprehensive dataset, designated as COD10K. This dataset encompasses over 10,000 images featuring objects camouflaged across diverse natural landscapes, covering 78 distinct object categories. Each image within COD10K is extensively annotated with category labels, bounding boxes, soft groupings, item instances, and levels of camouflage, laying a robust foundation for advancing research in several vision-based tasks, including image segmentation, object localization, and alpha-matting. Moreover, we introduce the Search Identification Network (SINet), a novel and efficient model tailored for COD. Demonstrating remarkable efficacy, SINet surpasses numerous state-of-the-art object detection benchmarks, including ANet, by achieving an unprecedented accuracy of 91.18% from a baseline of 81.23%.

Keywords: Camouflaged Object Detection (COD); image segmentation; SINet; Anet; Visual Recognition

1. Introduction

Camouflage represents a deliberate effort to obscure an object within a background frame, making it indistinguishable from its surroundings. This concept, originating from the animal kingdom's ancient practices, involves animals camouflaging themselves from predators by altering their body pattern, texture, and coloration to match the environmental textures [1]. Such adaptive changes are examples of biological camouflage, wherein animals modify their appearance to blend seamlessly with their environment, thereby evading detection. This process, often referred to as adaptive camouflage, confounds the observer's visual perception system, making the camouflaged entity difficult to discern. The challenge of recognizing camouflaged items is notably pronounced in the domain of Salient Object Detection (SOD), which typically focuses on identifying and highlighting the most visually prominent elements within an image. However, due to their effective blending with the environment, camouflaged objects elude easy detection, necessitating specialized approaches like COD that demand an in-depth understanding of visual perception mechanisms [2]. To address the scarcity of comprehensive research in COD, largely due to the absence of a substantial dataset, a collaborative effort by international scholars led to the development of the COD10K dataset. This dataset, a significant contribution to the field, consists of 10,000 images classified into 78 diverse categories, featuring a mix of backgrounds and objects in various states of concealment [3,4]. It employs a hierarchical structure for organization, assigning each image to a super category and subcategory, followed by meticulous annotation of bounding boxes and features such as indistinct boundaries or occlusions. Further detailed annotations for each object instance enhance the dataset's utility for research and development in COD.Tracking and defending endangered species, keeping an eye on illicit poaching, and managing wildlife habitats are all made possible by camouflaged object identification in environmental monitoring and animal conservation initiatives. These technologies support measures for sustainable development, research, and ecotourism by protecting biodiversity and natural ecosystems. These efforts benefit local businesses and communities financially. COD researchers face two primary challenges: the Intrinsic Similarity (IS) issue, where camouflaged objects share colors and patterns with their environment, complicating their detection; and the Edge Disruption (ED) problem, where the vague boundaries of objects prevent precise segmentation, even when rough localization is possible. Contemporary research endeavors aim to devise models that emulate the human visual system's capacity to navigate these challenges effectively [5]. COD holds significant potential for a wide array of real-world applications, including species discovery, image retrieval, traffic risk management, and medical image analysis, among others [6]. The evolutionary tactics of disruptive coloring and background matching, which animals use as anti-predator defenses, provide valuable insights for these applications. Disruptive coloring alters the prey's appearance by imitating background patterns to disrupt visual continuity, while background matching involves changing the prey's coloration to blend with the surrounding environment [7,8]. Camouflaged Object Detection is an intricate yet vital problem that spans the intersection of computer vision, biology, and technology, offering promising solutions for real-life challenges by leveraging the principles of natural camouflage.

This paper addresses the complex challenge of camouflaged object detection, where objects blend seamlessly into their environments, making them difficult to recognize. The main contribution of our work is a novel framework of the Search Identification Network (SINet), a novel deep learning model that significantly outperforms existing benchmarks with an accuracy of 91.18%. Through these contributions, our work not only advances the state of the art in camouflaged object detection but also lays the groundwork for future research aimed at enhancing detection capabilities in diverse and challenging environments.

2. Literature Review

The introduction of CAMO-CNN (a new method for human camouflage detection) addresses the complex challenge of accurately detecting human camouflage in surveillance scenarios. Identifying individuals who blend into their surroundings poses a significant concern for security and safety. CAMO-CNN utilizes the power of convolutional neural networks (CNNs) to improve detection accuracy in such contexts [9]. This study's findings indicate a significant enhancement in detection accuracy over previous methods, heralding a breakthrough in reliable human camouflage detection. This method's potential applications extend across various fields, including military and law enforcement, highlighting the remarkable capabilities of deep learning techniques, especially CNNs, in tackling the sophisticated problem of human camouflage detection. By enabling more accurate and efficient identification of concealed individuals, this approach significantly contributes to the enhancement of security and safety in surveillance operations [10]. Camouflaged object detection in aerial imagery research focuses on the critical challenge of detecting concealed objects within aerial imagery, an essential task in military and surveillance applications [11]. The primary issue revolves around the necessity to spot camouflaged objects from a bird's-eye view, where objects may be deliberately hidden to avoid detection [12,13]. The objective is to develop robust algorithms capable of consistently identifying camouflaged objects, thereby boosting situational awareness. The promising outcomes of this study demonstrate notable improvements in the capability to detect hidden objects in aerial imagery [14,15]. Such achievements carry significant implications for defense and security, empowering surveillance systems to uncover hidden threats from perspectives not readily accessible on the ground. Notably, this work highlights the crucial role of aerial detection in complementing ground-based systems, facilitating a more comprehensive surveillance network across numerous critical domains [16,17]. Addressing the intricate challenge of detecting camouflaged objects within dynamic environments where lighting, weather, and scene content can swiftly change is paramount [18,19]. The core issue involves creating detection algorithms that can effectively adapt to these evolving conditions. The aim of this research is to forge adaptive detection methods that maintain accuracy despite the dynamic nature of the environment. The findings are promising, indicating that the suggested adaptive algorithms show resilience to dynamic environments, leading to enhanced detection performance [20]. This adaptability proves especially valuable in unpredictable real-world scenarios, such as military operations and wildlife monitoring. The paper accentuates the importance of adaptability in detection systems, underscoring their capacity to remain effective across shifting landscapes and underscoring their vital role in improving situational awareness [21]. Additionally, the use of various lightweight segmentation architectures for feature extraction from image objects further underscores the advancement in detection techniques [22]. Transfer learning techniques like Efficient-Net deep learning architectures are used for extracting the features for object detection [23]. Deep learning conventional architecture like CNN is used for detection of camouflaged objects [24]. FINet, a lightweight COD frequency injection network that is effective. To bolster lightweight backbone features, FIM independently adds object-level and detailed frequency indications to RGB features. Extensive tests show that our FINet, with significantly faster speed and smaller model complexity, achieves competitive performance against most SOTA approaches [25]. The advancements in CAMO-CNN and other machine learning techniques for the detection of camouflaged objects represent significant strides in enhancing surveillance capabilities across diverse environments. The integration of adaptive algorithms and specialized segmentation architecture offers promising avenues for improving detection accuracy and adaptability, essential for meeting the security challenges of dynamic and complex landscapes. These innovations underscore the critical role of continuous technological evolution in maintaining a competitive edge in surveillance and defense strategies. The gap in the current discourse on camouflaged object detection, particularly with CAMO-CNN and related machine learning approaches, lies primarily in the need for further exploration and refinement of these technologies to address evolving camouflage techniques and dynamic environmental conditions. Despite the promising advancements, there remains a critical need to enhance the adaptability and efficiency of detection algorithms to anticipate and counter sophisticated evasion strategies employed by individuals and objects seeking to remain undetected. Additionally, the integration of these technologies into existing surveillance systems and their scalability across different operational scenarios poses ongoing challenges. Addressing these gaps through targeted research and development efforts is essential for advancing the field and ensuring robust, real-time detection capabilities in increasingly complex security landscapes.

3. Methodology

Data acquisition is the initial phase specified in architecture, as deep learning depends on the availability of data for decision-making. As shown in Figure 1. It includes gathering data, preparing case scenarios, and organizing them into groups based on specific characteristics relevant to the decision-making process. Then, the information is sent to the processing unit for further classification. This step is occasionally referred to as the "data pre-processing stage". The data model requires reliable, scalable, and fast discrete or continuous data. The information is then fed into batch data warehouses and stream processing systems for further processing or use in data modeling. The data processing unit is subsequently notified of the received data in the data acquisition layer. The features of the image objects are extracted automatically through the help of deep learning models and the entire dataset will be split into training and validation phase then after segmentation, the model is evaluated using metric measures like precision, recall, and F1 score.

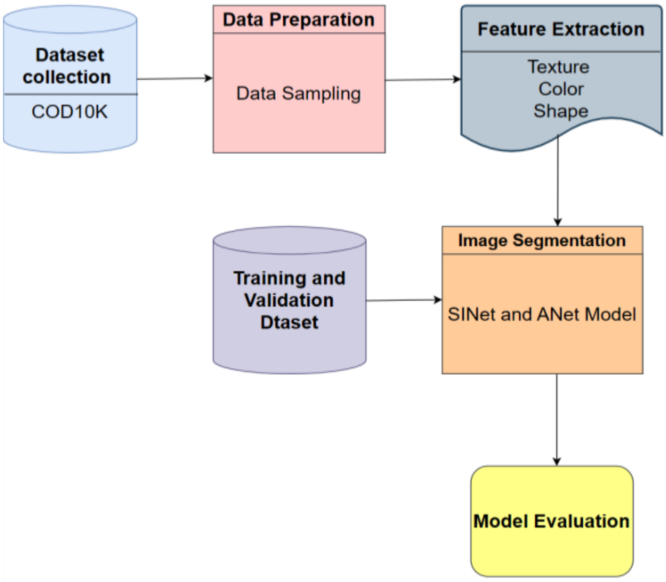

Figure 1. Methodology.

3.1. Dataset Description

Acquire relevant datasets that contain examples of both camouflaged and non-camouflaged objects. Data is pre-processed by performing tasks like resizing, normalization, and data augmentation to improve diversity and data quality. COD10K 2020 [26], the largest camouflaged object detection dataset so far, contains 10K images. It includes 5,066 camouflaged, 3,000 background, and 1,934 non-camouflaged images, divided into 10 super classes and 78 subclasses. The dataset will be divided into 6K images for training and 4K images for testing, randomly chosen from the entire dataset. Each object, in addition to the image array, contains some other attributes describing the object(s) in the image, as shown in Table 1.

Table 1. Description of Objects used in the COD10K Dataset.

Attributes	Description
MO	Multiple Objects. Image contains at least two objects
BO	Big Object, Ratio between object area and image area ≥ 0.5
SO	Small object Ratio between object area and image area ≤ 0.1
OV	Out of View. Object is clipped by image boundaries
OC	Occlusions. Objects are partially occluded
SC	Shape Complexity. Object contains thin parts (e.g. Animal foot)
IB	Indefinable Boundaries. The foreground and background areas around the object have similar colour (x^2 distance T_{gc} between RGB histograms less than 0.9)

3.2. Data Pre-Processing

Pre-processing is the procedure by which we modify our data before passing it through the algorithm. It allows raw data to be converted into clean data for collection. In other words, information collected from a variety of sources is frequently available in a raw format unsuitable for analysis. Real-world data might have noise, missing values, and inappropriate formats that cannot be utilized directly in machine learning models. Therefore, data pre-processing is necessary to clean the data and make it suitable for the model, aiming to improve the precision and effectiveness of a machine learning model.

3.3. Data Visualization

Data visualization plays a crucial role in camouflaged object detection by aiding understanding, evaluating the performance of detection algorithms, and making informed decisions. Visual representations of the data help project teams and stakeholders gain insight into the detection process. Typically, data visualization involves the creation of graphical representations, such as plots, charts, and images that convey information effectively. representations, such as plots, charts, and images, that convey information effectively. For example, histograms and scatter plots can be used to analyze the data distribution and relationships between different variables. Heat maps can illustrate the spatial distribution of detected objects within images or frames, aiding in the identification of patterns or anomalies. Additionally, visualizations of detection results, such as bounding boxes or overlays on original images, allow one to visually assess algorithm performance. Real-time visualization tools can also be used for live monitoring in surveillance applications. Effective data visualization not only enhances data exploration but also facilitates communication among team members and stakeholders, ensuring a deeper understanding of the camouflaged object detection process and the ability to make data-driven decisions for improvement and refinement.

3.4. Data Sampling

Data sampling is a set of techniques to reshape a training dataset so that classes are more evenly distributed. Once the dataset is balanced, standard machine learning algorithms can be used to train the adjusted dataset without making any adjustments.

3.5. Data Augmentation

A key tactic to improve the training dataset and models' capacity to apply their acquired features to fresh images is data augmentation. The creation of alternate image versions using various modifications while maintaining the underlying classification is known as image data augmentation. In order to allow models to learn from a wider variety of visual representations, these modifications include variations that mimic real-world situations and supplement the dataset with extra examples. Deep learning models demand large amounts of data, which makes data augmentation necessary. To improve the models' resilience and capacity for generalization, this study included rotation, flipping, zooming, cropping, brightness and contrast change, and noise-adding data augmentation. In order to replicate various orientations, the images were rotated by 40°. To enhance variety, images were rotated both vertically and horizontally. Additionally, the pictures were scaled at random to produce scale differences.

3.6. Proposed Framework

The framework proposed in this paper, called SINet (Search Identification Network), is inspired by the hunting operations of a predator. Biologists have shown that a predator will first search to determine whether potential prey exists (search), then identify the target (identify), and finally capture it. The network simulates the first two stages of hunting, including a Search Module (SM), which is responsible for searching for a camouflaged object, and an Identification Module (IM), which is used to precisely detect the camouflaged object. A SINet implementation using Tensor Flow and Keras features a Search Attention (SA) module to enhance middle-level features and obtain the enhanced camouflage map Ch:

$$Ch = fmax\ (g\ (X2,\ \sigma\ ,\lambda)\ CS\ ) \tag{1}$$

where g is the SA function, which is in our case a typical Gaussian filter with standard deviation $\sigma = 32$, and kernel size $\lambda = 4$, followed by a normalization operation. *fmax* () is a maximum function that highlights the initial camouflage regions of Cs, that is, those that were already extracted by the search module shown in equation 1. The technique of segmenting an image involves dividing the foreground from the background or grouping pixels according to their similarity in terms of color or shape. Figure 2 provides an overall overview of the network. The Search Module (SM) is located at the top left of the network. It consists of the first layers of the RESNet50 and four different receptive fields, each extracting different level features in the original image to detect whether a camouflaged object exists and its relative position in the image. The output of this module is then fed to the Partial Decoder Component (PDC) and then to the Search Attention function (SA) to highlight the areas that were already identified as candidates and passed to the Identification module. The Identification module combines two layers of the RESNet50 and three receptive fields, each extracting features of different levels. The result is then fed to another Partial Decoder. Component (PDC), producing the output of the Identification module, which is the final shape or edges of the camouflaged object.

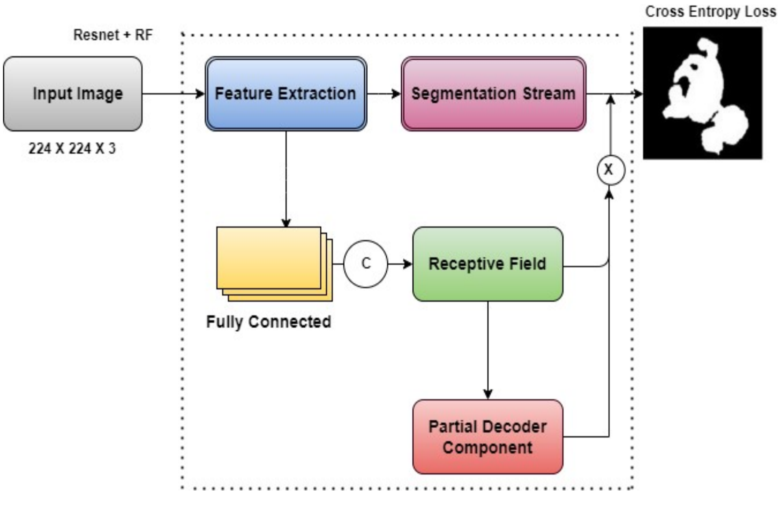

Figure 2. SINet Framework.

Since SINet has two outputs, it utilizes two losses: one for the Search Module and one for the Identification Module. Both employ Cross-Entropy losses, with the total loss being the sum of the losses from the search module and the identification module, as depicted in Equation (2), given G the ground truth.

$$L = CE\ (Ccsm,\ G) + Li \quad CE\ (Ccim,\ G) \tag{2}$$

Training a model over multiple epochs provide insights into the model's performance, including loss values for both the training and validation datasets across each epoch. At the first epoch, out of a total of 40 epochs, the SM_loss is 0.4125 and IM_loss is 0.4279. These figures represent specific components of the total loss, indicating that the total loss comprises SM_loss and IM_loss. These metrics likely reflect different aspects or objectives of the training process, with the aim of minimizing both. The typical goal is to observe a decrease in training loss and maintain a low validation loss, suggesting that the model is learning from the data and generalizing well to new, unseen data. Figure 3. displays the training loss plot, where the x-axis denotes the training epochs (the number of times the entire training dataset was processed by the model), and the y-axis shows the corresponding training loss values for each epoch. This plot offers valuable insights into the model's training loss reduction or convergence over time, usually exhibiting a downward trend in the loss curve as the model learns and improves.

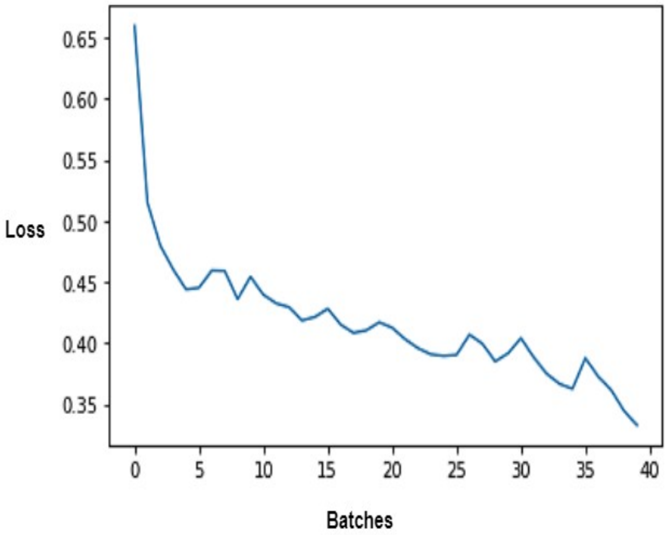

Figure 3. Model Training Loss.

The graph presents three-line plots side by side, each illustrating a different type of loss value: total loss, search loss, and identification loss, across a series of batches. This single figure comprises three subplots, with each one depicting the progression of a distinct type of loss—total, search, and identification—throughout various batches during model training. The variable k enables the initiation of the graph from a specific batch number, facilitating targeted analysis of segments of the training process as shown in Figure 4, Figure 5 and Figure 6.

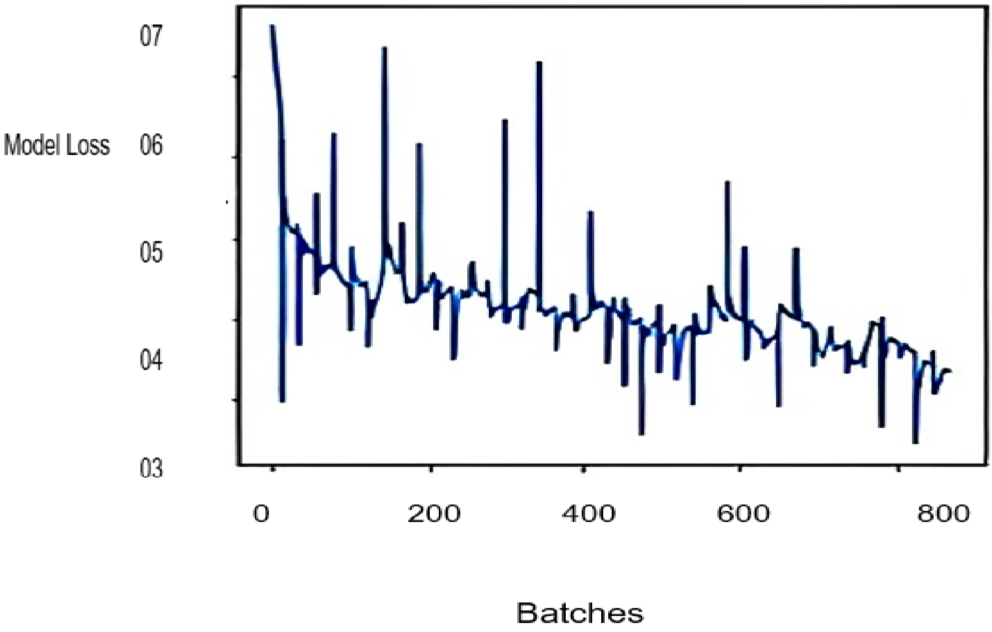

Figure 4. Model Total Loss.

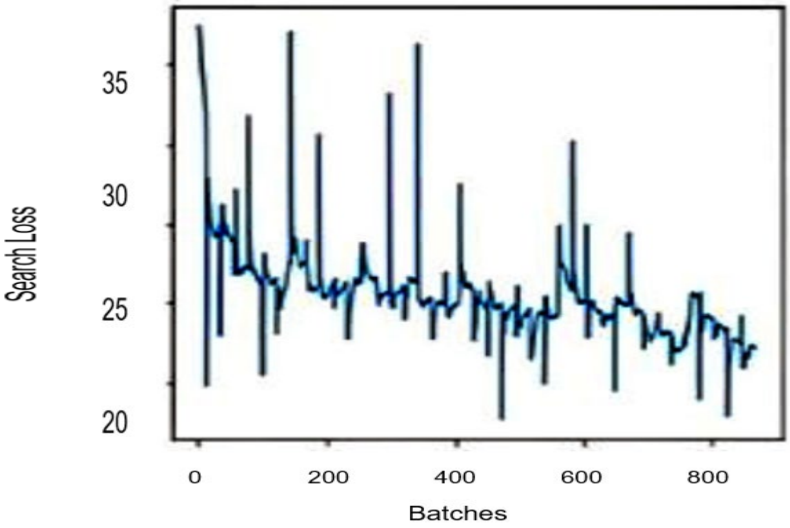

Figure 5. Model Search Loss.

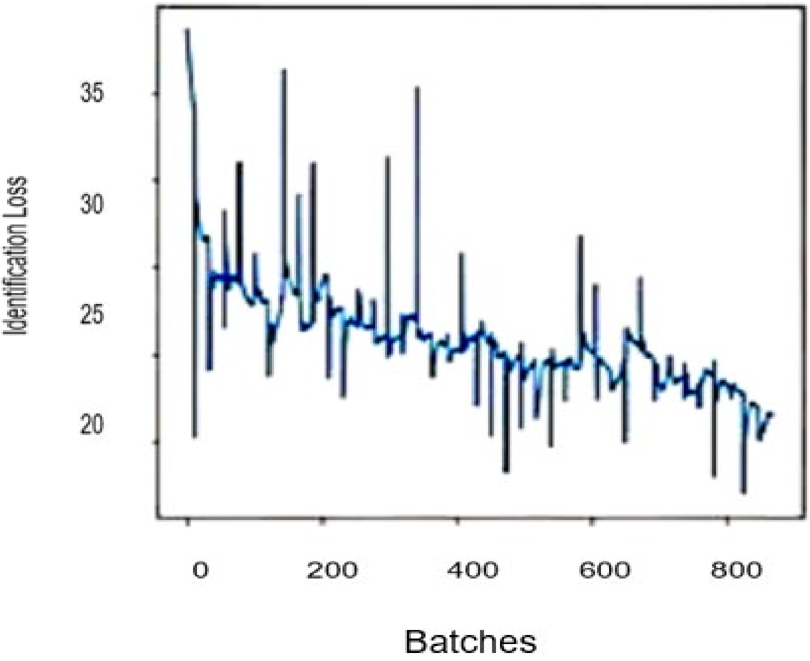

Figure 6. Identification Loss.

The principal evaluation metric used in the paper is the mean absolute error, as it assesses the pixel-level accuracy between the predicted MAP and the ground truth. Ultimately, we achieved a mean absolute error of 0.1668 for the Search Module and 0.1306 for the Identification Module. Observing the loss during training also provided interesting insights illustrates the progression of the total and the two losses over the training batches. Sharp edges are observed, attributable to the structure of the RESNet50, which contains many residual blocks causing the loss to fluctuate. Nonetheless, the general trend seems to converge smoothly. The ANet (Anabranch1 Network), another framework presented in this paper, draws inspiration from a predator's methods of capture. ANet is an efficient, flexible, conceptually straightforward, and comprehensive network for camouflaged object detection shown in Figure 7.

The ANet utilizes two distinct network models: the classification network model, based on a convolutional neural network (CNN), and the segmentation network model, which relies on a fully convolutional network (FCN) as shown in Figure 8. The CNN provides insights into whether the input image contains a camouflaged object by generating object hypotheses within the image. In contrast, the FCN delivers semantic information at the pixel level, allowing for a detailed understanding of the image's content. The output of the FCN is regarded as the semantic details of the various items in the picture, enriching the model's capability to analyze and interpret the visual data accurately.

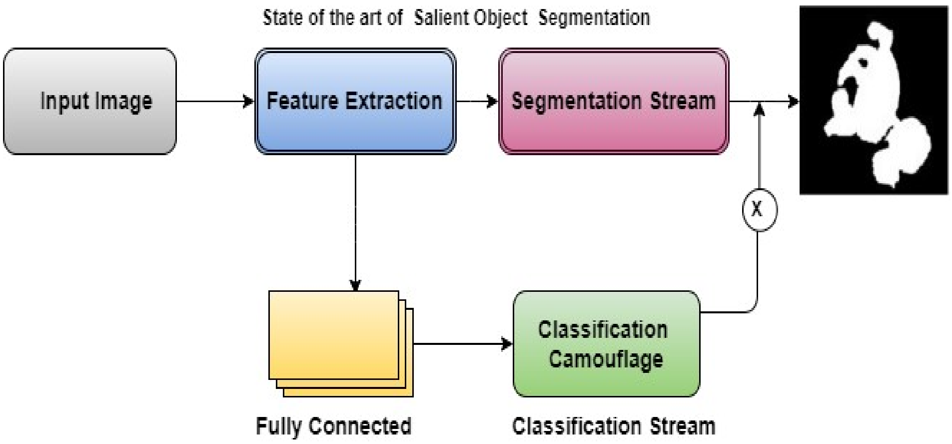

Figure 7. Anet Framework.

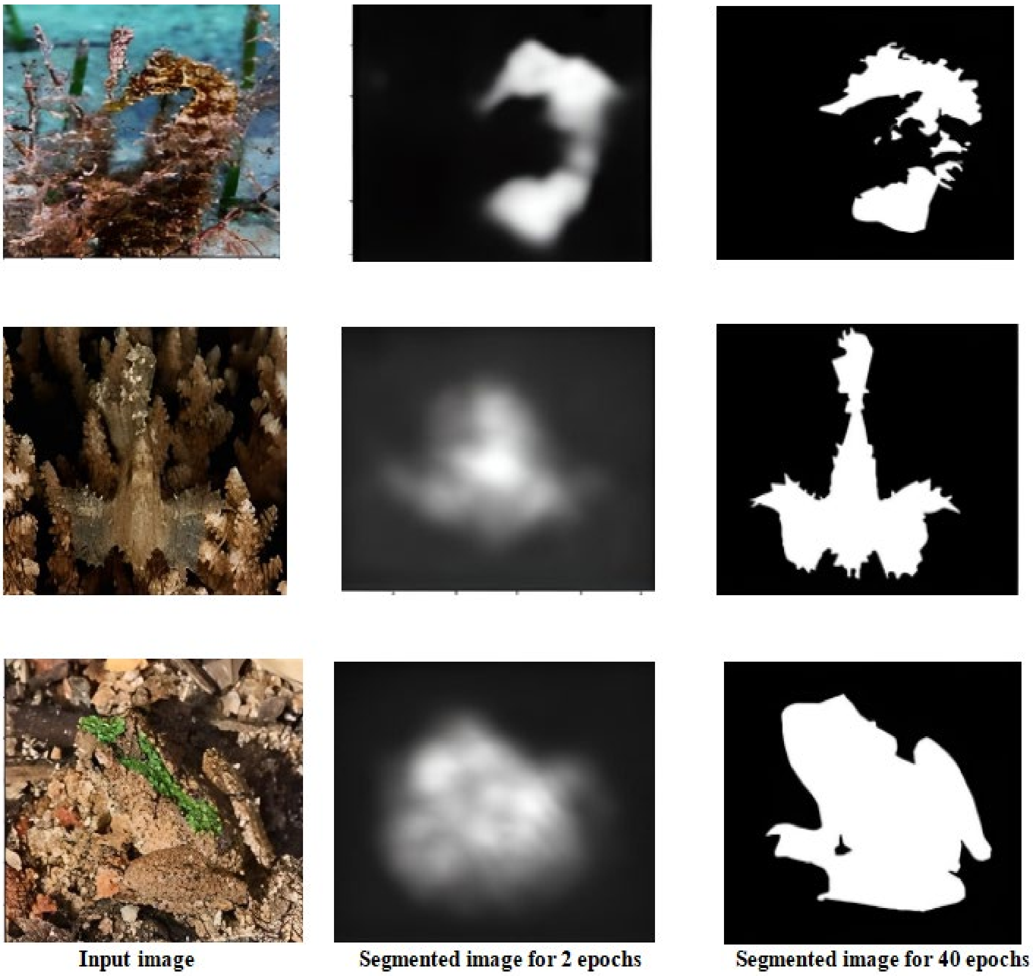

Figure 8. Sample Segmentation Using SINet.

As shown in Figure 8, in the initial stages, such as after just two epochs, the SINet performance is evidently limited. At this point, the network struggles to distinguish between various elements within the image. This difficulty in differentiating between the components highlights the initial challenges the SINet faces in understanding the complex interplay of objects and their surroundings. However, as training progresses over 40 epochs, discernible improvements become apparent. The SINet focus starts to shift towards identifying the location of the concealed object. While it is still not entirely capable of precisely determining the object's shape and rendering it in detail, there is a noticeable shift in attention towards pinpointing the object's position.

4. Results and Discussion

The adaptability of the SINet system to dynamic environments is a crucial aspect as discussed above. This adaptability allows the system to perform reliably in scenarios where conditions such as lighting, weather, or scene content change rapidly. The proposed work was experimented with 8 GB RAM, GeForce RTX30 ***Gpu***. It is vital for ensuring that detection accuracy remains high, regardless of the deployment environment. Architectures like SINet and ANet have achieved accuracy of 91.18% and 82.23%, with the training and test ratio split of 80:20 for both the models respectively. At this point, SINet has demonstrated its proficiency in recognizing camouflaged objects, marking a significant achievement compared with ANet. In these images, the SINet not only detects the presence of concealed objects but also provides a semblance of their shape and various components. The ability to discern the concealed object's form and structural elements represents a significant advancement in the system's capabilities, suggesting that our SINet has acquired the ability to penetrate camouflage, offering valuable insight into the composition and structure of hidden objects. These results hold considerable promise and represent a step forward in the field of camouflaged object detection, with potential applications in security, surveillance, and beyond. The segmentation of the images is shown in Figure 9 below.

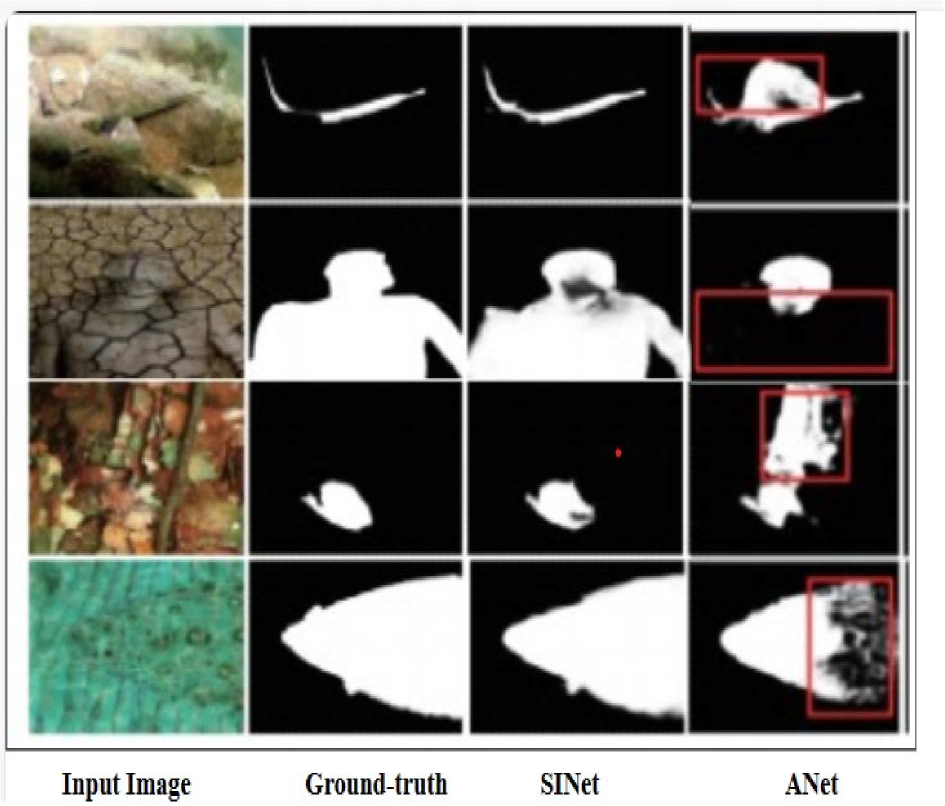

Figure 9. Sample segmentation using SINet and Anet.

The comparison of training the model using several deep learning architectures, such as Anet and SINet, is displayed as in Table 2. The SINet has higher accuracy, preciousness, recall, and F1 score than the Anet, according to the values shown in Table 2. The ANet's accuracy declined because of some characteristics that made it harder to segregate the concealed objects, which includes the background clutter, shape complexity, object occlusion, and distraction. Conversely, SINet obtained superior results to segregate the concealed objects with this feature.

Table 2. The Performance Measures Using on the COD10K Dataset.

Model	Accuracy	Precision	Recall	F1-Score
[19]	80.40	79.60	80.30	80.40
[22]	80.60	79.90	79.97	80.60
ANet	82.23	81.72	81.36	82.42
[20]	88.80	87.35	87.56	88.80
SINet	**91.18**	**90.48**	**90.84**	**92.75**

5. Potential Limitations

While our study demonstrates significant advancements in camouflaged object detection through the introduction of SINet and the COD10K dataset, there are certain limitations that merit discussion:

1. **Dataset Specificity:** The COD10K dataset, while extensive, primarily focuses on natural environments. This specificity may limit the generalizability of the findings to other scenarios, such as urban or industrial settings, where camouflage characteristics differ significantly.
2. **Computational Requirements:** The implementation of SINet involves substantial computational resources, including high-end GPUs and significant memory capacity. These requirements may pose a barrier to adoption for organizations with limited access to such resources.
3. **Real-Time Application Challenges:** Although SINet achieves high accuracy, the model's computational complexity may impede real-time application, particularly in dynamic environments requiring immediate detection and response.
4. **Dependence on Preprocessing:** The data preprocessing steps, including normalization and augmentation, play a critical role in model performance. Variability in preprocessing practices could potentially impact the reproducibility of the results.
5. **Limited Exploration of Environmental Variability:** While the dataset includes diverse natural landscapes, it does not comprehensively cover all environmental conditions, such as extreme weather or lighting variations, which could affect model performance.
6. **Evaluation Metrics:** The study primarily utilizes standard metrics like absolute error, precision, recall, and F1-score. Additional metrics, such as intersection-over-union (IoU) or robustness measures under adversarial conditions could provide a more holistic evaluation of the model's effectiveness.

6. Conclusion

The anticipated conclusion of camouflaged object detection encompasses several key objectives and future directions. The primary goal is to introduce a novel deep learning model designed specifically for the effective detection of camouflaged objects within natural environments. This model, developed through the proposed methodology, aims to address critical issues in camouflaged object detection. First, the endeavor is to enhance detection accuracy, with a specific focus on reducing false positives. Achieving this would significantly improve the system's reliability in distinguishing concealed objects from their surroundings, thus enhancing its real-world utility. Comparisons between architectures like SINet and ANet were made, observing accuracy of 91.18% and 82.23%, respectively, wherein SINet outperformed ANet architecture by fine-tuning the hyperparameters at the architecture level. This efficiency is crucial to ensure that the model can perform detection tasks quickly and without excessive computational demands, making it practical for real-time applications. The successful completion of this work holds great promise for the field of camouflaged object detection, signifying a notable advancement and offering improved detection capabilities with potential applications extending to diverse domains, including wildlife monitoring and beyond. Future scope can be determined by working on various deep net architectures and by fine-tuning the hyperparameters to increase the accuracy of the model.

Author Contributions

Conceptualization, M.N. and A.D.; methodology, N.A.; software, M.S.; validation, N.A., M.S and M.N.; formal analysis, N.A.; investigation, A.A.; resources, M.S.; data curation, N.A.; writing—original draft preparation, A.A.; writing—review and editing, A.D.; visualization, A.A.; supervision, M.N.; project administration, A.D.; funding acquisition, A.D. All authors have read and agreed to the published version of the manuscript. Authorship must be limited to those who have contributed substantially to the work reported.

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Conflict of Interest Statement

The authors have no conflicts of interest to declare.

Data Availability Statement

Data available on [26].

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References

1. Fan, D. P., Ji, G. P., Sun, G., Cheng, M. M., Shen, J., & Shao, L. (2020). Camouflaged object detection. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 2777-2787).
2. Xu, X., Zhu, M., Yu, J., Chen, S., Hu, X., & Yang, Y. (2021). Boundary guidance network for camouflage object detection. *Image and Vision Computing*, 114, 104283.
3. Huang, L., Gao, C., Zhou, Y., Xie, C., Quille, A. L., Zou, C., & Liu, N. (2020). Universal physical camouflage attacks on object detectors. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 720-729).
4. Hu, S., Zhang, Y., Laha, S., Sharma, A., & Foroosh, H. (2021, January). Cca: Exploring the possibility of contextual camouflage attack on object detection. In *2020 25th International Conference on Pattern Recognition (ICPR) (pp. 7647-7654)*. IEEE
5. Zheng, Y., Zhang, X., Wang, F., Cao, T., Sun, M., & Wang, X. (2018). Detection of people with camouflage pattern via dense deconvolution network. *IEEE Signal Processing Letters*, 26(1), 29-33
6. Deng, B., Zhang, D., Dong, F., Zhang, J., Shafiq, M., & Gu, Z. (2023). Rust-Style Patch: A Physical and Naturalistic Camouflage Attacks on Object Detector for Remote Sensing Images. *Remote Sensing*, 15(4), 885.
7. Krishna Chaitanya, G., & Maragatham, G. (2021). Object and obstacle detection for self-driving cars using GoogLeNet and deep learning. In *Artificial Intelligence Techniques for Advanced Computing*
8. Saha, A., & Thomas, K. T. (2022). Fake News Detection using Machine Learning and Deep Learning Hybrid Algorithms. In *Data Science and Security: Proceedings of IDSCS 2022* (pp. 447-456). Singapore:
9. Sorin, V., Barash, Y., Konen, E., & Klang, E. (2020). Deep learning for natural language processing in radiology—fundamental and a systematic review. *Journal of the American College of Radiology*, 17(5)
10. Vishnu, R., & Krishna Prakash, N. (2022). Mobile application-based virtual assistant using deep learning. In *Soft Computing and Signal Processing: Proceedings of 3rd ICSCSP 2020*, Volume 2 (pp. 609-617). Springer Singapore.
11. Chou, C. H., Su, Y. S., Hsu, C. J., Lee, K. C., & Han, P. H. (2020). Design of desktop audiovisual entertainment system with deep learning and haptic sensations. *Symmetry*, 12(10), 1718.
12. Chou, C. H., Su, Y. S., Hsu, C. J., Lee, K. C., & Han, P. H. (2021). Design of desktop audiovisual entertainment system with deep learning and haptic sensations. *Symmetry*, 12(10), 1718.
13. Pathak, A. R., Pandey, M., Rautaray, S., & Pawar, K. (2018). Assessment of object detection using deep convolutional neural networks. In *Intelligent Computing and Information and Communication: Proceedings of 2nd International Conference*, ICICC 2017 (pp. 457-466). Springer Singapore.
14. Saba, L., Biswas, M., Kuppili, V., Godia, E. C., Suri, H. S., Edla, D. R., ... & Suri, J. S. (2019). The present and future of deep learning in radiology. *European journal of radiology*, 114, 14-24.
15. He, C., Li, K., Zhang, Y., Tang, L., Zhang, Y., Guo, Z., & Li, X. (2023). Camouflaged object detection with feature decomposition and edge reconstruction. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 22046-22055).
16. Yang, Y., & Zhang, Q. (2023). Finding Camouflaged Objects along the Camouflage Mechanisms
17. Lv, Y., Zhang, J., Dai, Y., Li, A., Barnes, N., & Fan, D. P. (2023). Towards deeper understanding of camouflaged object detection. *IEEE Transactions on Circuits and Systems for Video Technology*.
18. Li, H., Feng, C. M., Xu, Y., Zhou, T., Yao, L., & Chang, X. (2023). Zero-Shot Camouflaged Object Detection. *IEEE Transactions on Image Processing*.
19. Zhang, Y., Zhang, J., Hamidouche, W., & Deforges, O. (2023). Predictive Uncertainty Estimation for Camouflaged Object Detection. *IEEE Transactions on Image Processing*.
20. Lv, Y., Zhang, J., Dai, Y., Li, A., Barnes, N., & Fan, D. P. (2023). Towards deeper understanding of camouflaged object detection. *IEEE Transactions on Circuits and Systems for Video Technology*.
21. Esteva, A., Feng, J., van der Wal, D., Huang, S. C., Simko, J. P., DeVries, S., ... & Mohamad, O. (2022). Prostate cancer therapy personalization via multi-modal deep learning on randomized phase III clinical trials. NPJ Digital Medicine, 5(1), 71. personalization via multi-modal deep learning on randomized phase III clinical trials. *NPJ Digital Medicine*, 5(1), 71.
22. Li, Q., Wang, Z., Zhang, X., & Du, H. (2024). Lightweight camouflaged object detection model based on multilevel feature fusion. *Complex & Intelligent Systems*, 1-11.
23. Wen, Y., Ke, W., & Sheng, H. (2024). Camouflaged Object Detection Based on Deep Learning with Attention-Guided Edge Detection and Multi-Scale Context Fusion. *Applied Sciences*, 14(6), 2494.
24. Liang, Y., Qin, G., Sun, M., Wang, X., Yan, J., & Zhang, Z. (2023). A systematic review of image-level camouflaged object detection with deep learning. *Neurocomputing*, 127050.
25. Liang, W., Wu, J., Wu, Y., Mu, X., & Xu, J. (2024). FINet: Frequency Injection Network for Lightweight Camouflaged Object Detection. *IEEE Signal Processing Letters*.
26. Available at: https://www.kaggle.com/datasets/getcam/cod10k (Accessed on date: 01 October 2024).

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