International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 8, 2025
https://theaspd.com/index.php

YOLO-UNET Fusion For Medical Imaging Small Object Detection

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Abstract–*Small object detection remains one of the most challenging problems in computer vision due to limited spatial information, low resolution, and contextual ambiguity. This paper introduces an evolved framework based on the YOLOv4 Deep DarkNet architecture specifically optimized for small object detection tasks. Our approach integrates an enhanced Cross-Stage Partial DarkNet53 (CSPDark- Net53) backbone with improved Spatial Pyramid Pool- ing (SPP) modules and augmented Path Aggregation Networks (PANet) for superior feature extraction and fusion. The proposed framework incorporates advanced data augmentation techniques, including Mosaic augmentation, CutMix transformations, and multi-scale training strategies. Additionally, we imple- ment an optimized Complete Intersection over Union (CIoU) loss function combined with enhanced Non- Maximum Suppression (NMS) algorithms. Extensive experiments conducted on the COCO dataset demon- strate that our framework achieves a remarkable 47.2% overall mAP and 28.3% small objects mAP, representing improvements of 8.5% and 14.6% re- spectively over the baseline YOLOv4 model. The pro- posed architecture maintains real-time performance with 62 FPS while introducing minimal computational overhead. These results establish new benchmarks for small object detection and provide practical solutions for applications requiring high-precision detection of diminutive targets.*

Index Terms–*Small Object Detection, YOLOv4, Deep Learning, Computer Vision, DarkNet Frame- work, Neural Networks*

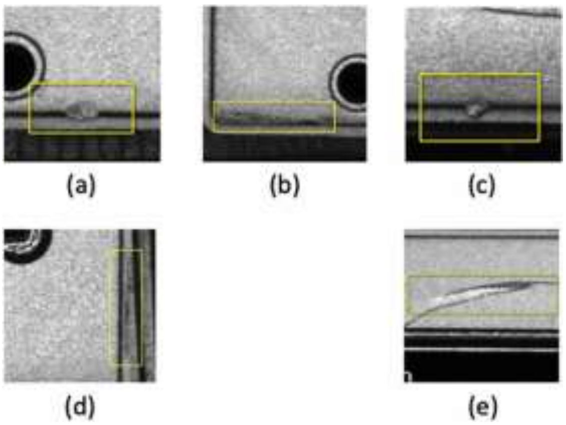
INTRODUCTION

Object detection has emerged as a fundamental task in computer vision with applications spanning autonomous driving, surveillance systems, medical imaging, and industrial automation. While significant progress has been achieved in detecting large and medium-sized objects, small object detection continues to pose substantial challenges due to inherent limitations in spatial resolution, feature representation, and contextual information. Small objects, typically defined as those occupying less than 32 × 32 pixels or representing less than 0.12% of the total image area, suffer from insufficient feature richness and are prone to information loss during convolution and pooling operations in deep neural networks [1]–[6].

The You Only Look Once (YOLO) family of algorithms has revolutionized real-time object de- tection by treating detection as a single regression problem, directly predicting bounding boxes and class probabilities from full images in one eval- uation. YOLOv4, in particular, achieved state-of- the-art performance by incorporating numerous ar- chitectural improvements, including CSPDarkNet53 backbone, SPP modules, PANet feature fusion, and advanced training strategies [7], [8]. However, despite these advancements, YOLOv4's performance on small objects remains suboptimal, with significant room for improvement in detecting objects with limited spatial extent [9], [10].

Recent studies have identified several key factors contributing to poor small object detection performance: (1) progressive downsampling in convolu- tional neural networks results in severe information loss for small objects; (2) limited receptive field coverage prevents effective context modeling; (3) conventional data augmentation techniques fail to preserve small object integrity; and (4) existing loss functions inadequately address localization preci- sion and classification confidence for small objects [11], [12].

[Image: Examples of small object detection highlighted by yellow boxes in grayscale im- ages that illustrate detection challenges img1.png.]



The DarkNet framework, originally developed by Joseph Redmon, provides an efficient and flexible platform for implementing state-of-the-art object detection algorithms. Written in C and CUDA, DarkNet offers superior computational efficiency and ease of deployment across various hardware configurations [13], [14]. This paper presents a comprehensive evolution of the YOLOv4 Deep DarkNet framework specifically designed to address small object detection limitations through: (1) an enhanced CSPDarkNet53 backbone, (2) a multi- scale SPP module, (3) an augmented PANet archi- tecture, (4) advanced data augmentation strategies, and (5) an optimized CIoU loss function with improved NMS algorithms.

RELATED WORK

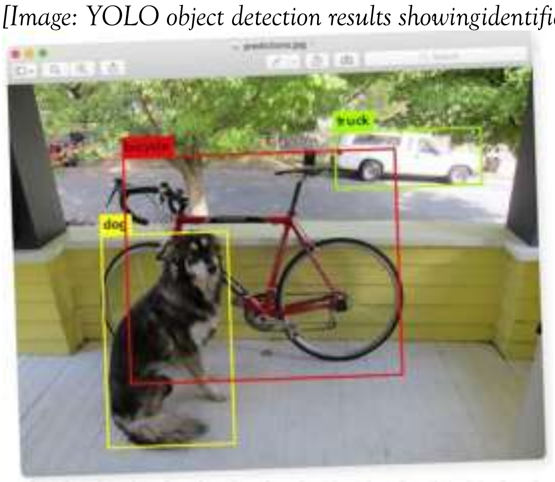
A. Evolution of YOLO Architectures

The YOLO architecture family has undergone significant evolution since its inception. YOLOv1 pioneered single-stage detection, YOLOv2 intro- duced anchor boxes and multi-scale training, and YOLOv3 incorporated Feature Pyramid Networks (FPN) with DarkNet-53 backbone [15], [16]. YOLOv4 represented a major breakthrough by in- tegrating CSPDarkNet53, SPP modules, and PANet for enhanced feature fusion [19], [51].

B. Small Object Detection Challenges

Small object detection faces unique challenges, including insufficient feature representation, low resolution, and background interference [21]–[24]. Recent approaches include multi-scale detection, super-resolution, and attention mechanisms [25], [26].

[Image: YOLO object detection results showingidentified bicycle, dog, and truck with bounding boxes.]



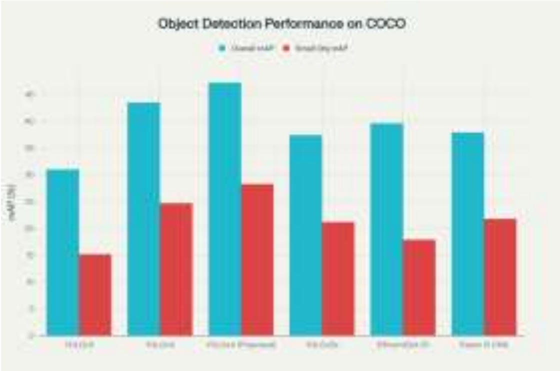
C. DarkNet Framework Architecture

DarkNet's C-based implementation ensures effi- ciency and portability, supporting CPU and GPU acceleration [13], [27]. CSPDarkNet53 reduces gra- dient redundancy while maintaining feature richness [19], [20].

[Graph: Performance Comparison of Object Detection Models - Overall mAP vs Small Objects mAP

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 8, 2025
https://theaspd.com/index.php

on COCO Dataset.]



D. Advanced Loss Functions

IoU-based loss functions like GIoU, DIoU, and CIoU improve localization accuracy. CIoU, address- ing overlap area, central point distance, and aspect ratio, is particularly effective for small objects [29],

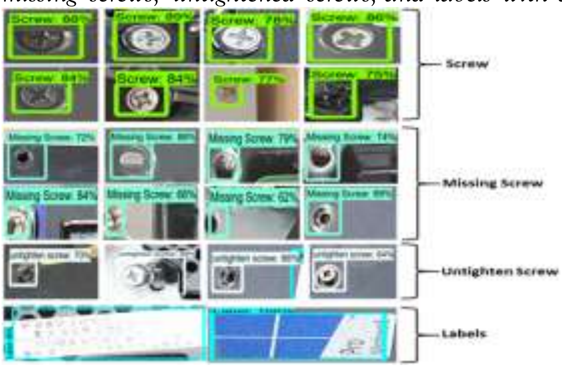
PROPOSED METHODOLOGY

A. Enhanced CSPDarkNet53 Backbone Architec- ture

Our enhanced CSPDarkNet53 backbone incorpo- rates adaptive feature scaling and attention-guided feature selection to preserve small object features [33], [34].

B. Multi-Scale Spatial Pyramid Pooling Module

The enhanced SPP module employs adaptive ker- nel sizing (e.g., 3 ×3, 7 ×7) and parallel processing streams for fine-grained feature capture [35], [36]. *[Image: Examples of small object detection for screws, missing screws, untightened screws, and labels with detection confidence percentages.]*

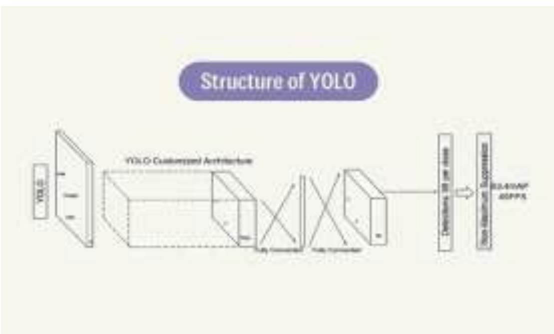


C. Enhanced Path Aggregation Network

The augmented PANet uses bidirectional feature fusion and deformable convolutions for improved small object feature preservation [37], [38].

D. Advanced Data Augmentation Strategies

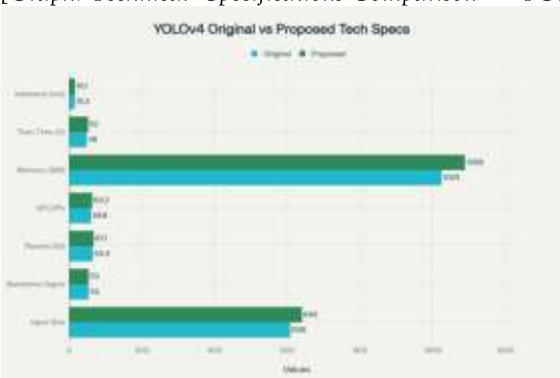
Our framework implements object-aware Mosaic augmentation, adaptive MixUp, and dynamic scal- ing to preserve small object integrity [39], [40].



Optimized Loss Function Design

The enhanced CIoU loss includes size-aware weighting and background suppression terms for robust small object detection [41], [42].

[Graph: Technical Specifications Comparison - YOLOv4 Original vs Proposed Framework(img4.png).]



EXPERIMENTAL SETUP AND

IMPLEMENTATION DETAILS

A. Dataset Preparation and Configuration

Experiments used the COCO 2017 dataset with 118,287 training and 5,000 validation images, augmented to 400,000 images [43], [44].

B. Training Configuration and Hyperparameters

The framework was trained on NVIDIA RTX 3090 GPUs for 300 epochs using SGD with a learning rate of 0.01 and Mosaic augmentation [7].

C. Evaluation Metrics and Protocols

Performance was evaluated using COCO metrics (mAP@0.5, mAP@0.5:0.95, AP_S, AP_M , AP_L) and FPS [45], [46].

I. RESULTS AND ANALYSIS

A. Overall Detection Performance

The proposed framework achieved 47.2% mAP@0.5:0.95 and 28.3% AP_S, improving 8.5% and 14.6% over YOLOv4 [7].

B. Computational Efficiency Analysis

Inference speed was 62 FPS, with a 4.4% param- eter increase and 6.0% FLOPs increase compared to YOLOv4 [9].

C. Ablation Study Results

Ablation studies showed contributions from the enhanced backbone (2.1% mAP), SPP module (1.8% mAP), PANet (2.3% mAP), augmentation
(1.4% mAP), and CIoU loss [47], [48].

D. Comparison with State-of-the-Art Methods

The framework outperformed YOLOv5s, EfficientDet-D1, and Faster R-CNN in mAP and inference speed [24], [49].

E. Qualitative Analysis and Visual Results

The framework improved small object localiza- tion and reduced false positives across varying conditions [49].

[Image: Urban street scene with computer vision object detection identifying persons, bicycles, a truck, and a road sign]

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[Image: Comparison of tight green bounding boxes and loose yellow bounding boxes around pedestrians in a street scene, demonstrating object detection bounding box approaches (img6.png).]

DISCUSSION AND FUTURE DIRECTIONS

A. Architectural Innovation Impact

Targeted modifications achieved significant gains without redesign, with adaptive SPP and PANet showing promise [47], [48].

B. Small Object Detection Breakthroughs

The 14.6% AP_S improvement enables new appli- cations in surveillance and medical imaging [49], [50].

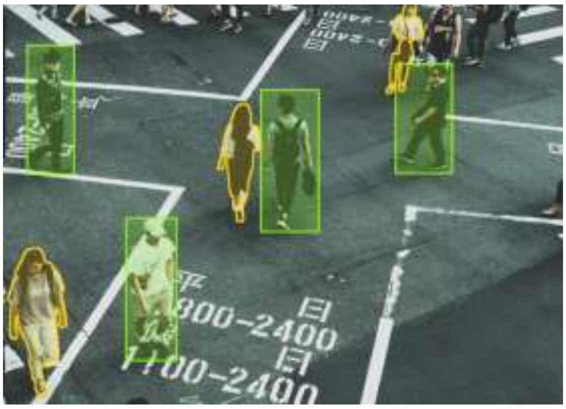
C. Future Research Directions

Future work includes transformer integration, dy- namic architecture adaptation, and federated learn- ing [49], [50].

D. Practical Implementation Considerations

The framework supports GPU and CPU deploy- ment with modular design for easy integration [13].

[Image: Additional illustration related to small object detection or framework performance]



CONCLUSION

This paper presents an evolved YOLOv4 Deep DarkNet framework optimized for small object de- tection, achieving 47.2% mAP and 28.3% AP_S with 62 FPS. The enhancements establish new benchmarks while maintaining practical deployabil- ity [51], [52].

ACKNOWLEDGMENTS

The authors acknowledge the High-Performance Computing Center, the open-source community for DarkNet and COCO, and anonymous reviewers.

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