# **Enhanced YOLOv5 for Efficien**<br>Debris Detection<br>Shicheng Li, Xiaoxia Zhang, Ruiqing Shan<br>Abstract—To address the issue of large model parameter size<br>of the weight of biofoulir<br>d computational complexity in existing garbage Enhanced YOLOv5 for Efficient Marine<br>Debris Detection<br>Shicheng Li, Xiaoxia Zhang, Ruiqing Shan<br>With the weight of biofouling, can lose buoyancy and sink to Engineering Letters<br>
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underwater mobile devices, we propose an improve *Abstract*—To address the issue of large model parameter size<br>
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underwater mobile devices, we propose an impr *is modified* **to** *EI* **and the section of the search of biofs and computational complexity in existing garbage detection by underwater operationolels deployed on underwater embedded devices or manual methods, which underwa** *Abstract***—To address the issue of large model parameter size the scabed [2]. However, due of convertions, models deployed on underwater embedded devices or underwater mobile devices, we propose an improved YOLOVS nettain Trash-ICRA19 dataset.** The results indicate that the mean specifical depiction of the properties of the seabled action and computational complexity in existing garbage detection manual methods, which in underwater mobile and computational computative in existing gaming centerion<br>
and delivered on underwater embedded devices or<br>
underwater mobile devices, we propose an improved YOLOv5<br>
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network based on lightweight mechanism. Firstly, lightweight<br>
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C3-Faster and Ghost conv with smaller parameter metrware mome everes, we propose an improved vDLOv's<br> **reduced on lightweight mechanism.** Firstly, lightweight trash still faces signif<br>
C3-Faster and Ghost conv with smaller parameters and trash still faces signif<br>
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C3-Faster and Ghost conv with smaller parameters and this still faces signific<br>
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computational complexity are adopted to replace the original<br>
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C3 module and some Conv modules in the YOLOv5s networ **Examplerational complexity are aboved to replace the original computer and some Conv modules in the YOLOv5s network.** Hinton in 2012 [3], Secondly, a squeeze-and-excitation (SE) attention mechanism is an era of rapid embe **Example and some Conv modules in the YOLOVS HEWITE.** Thin to the secondly, a squeeze-and-excitation (SE) attention mechanism is an era of rapid expandibilities. Finally, the bounding box regression loss function occurred **decoming a support of the control of the control of the control of the method of the bunding box regression loss function**<br> **dependent in 2016** when the network to enhance feature extraction<br>
is modified to *EloU* loss fu **detection. INTRONISTION**<br> **INTRONISTER SET INTERVALUAT SERVIT ALLOWS** and interact that the mean<br> **INSURGENT CRAIP dataset.** The results indicate that the mean<br> **INSURGENT CRAIP dataset.** The results indicate that the mean<br> **INSURGE EXECUTE:** Attentional mechanism, *EIOU* Overage Precision of the original YOLOv5s, the optimized algorithm<br>
reduced the parameter size by 35% and achieved a processing adaptability,<br>
reduced the parameter size by 35% and The intervalse of the material and transform and the proposed can develop more efficient underwa d of over 40 frame/s, meeting the real-time detection<br>
irefrective method for replicative method can develop more efficient underwater<br>
internents. This research indicates that the proposed<br>
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mprovement method can develop more efficient underwater<br>
autonomous underwater vehicle<br>
devices, providing better support for real-time marine debris using autonomous intelligent<br>
devices, providing better support for real gaing to the minimum state of embedded text and threat to end the significant in the significant in the significant threat to end of the minimum state of the minimum state of and reliable target information in completing g index **Example Society.** The state support of the tant due maint desires and policing the defection.<br>
In a efficient method of the state of the *Index Terms*—Underwater garbage, Yolov5s, C3-Faster,<br>
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The presence of garbage in underwater environments not<br>
only poses a significant therat to ecosystems but also has<br>
indirect negative impact Manuscript received Sep 9, 2023; revised of Computer Science and Scitter September September 2.74 and the september of the waste of the Water of Irrect negative impacts on human society. Consequently,<br>
s issue demands immediate attention and resolution.<br>
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Ilghtweight networks, F-<br>
ilght this issue demands immediate attention and resolution.<br>
Software engines including beaches, sea surfaces, seabeds, and marine life.<br>
Currently, mainstream approaches to studying marine debris<br>
cleanup have focused on treat Marine debris is pervasive across various marine habit<br>including beaches, sea surfaces, seabeds, and marine 1<br>Currently, mainstream approaches to studying marine del<br>cleanup have focused on treating beaches and floating de Example the computer Science and Technology LiaoNing, Anshan, Box of School of Computer Science and Rotting Shan is a Potersponding author, phone:86-0412-5929812; e-mail:<br>Rainiya Shan is a Professor of School of Computer S Including beaches, sea surfaces, seabeds, and marine file.<br>
Currently, mainstream approaches to studying marine debris<br>
cleanup have focused on treating beaches and floating debris;<br>
the reality is that nearly seventy perc Currently, mainstream approaches to studying marine debris<br>
cleanup have focused on treating beaches and floating debris;<br>
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the seabed [1]. Even low-density

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for Efficient Marine<br>etection<br>Zhang, Ruiqing Shan<br>with the weight of biofouling, can lose buoyancy and sink to<br>the seabed [2]. However, due to the unique challenges posed<br>by underwater operations, cleanup efforts often rel for Efficient Marine<br>etection<br>Zhang, Ruiqing Shan<br>with the weight of biofouling, can lose buoyancy and sink to<br>the seabed [2]. However, due to the unique challenges posed<br>by underwater operations, cleanup efforts often rel for Efficient Marine<br>etection<br>Zhang, Ruiqing Shan<br>with the weight of biofouling, can lose buoyancy and sink to<br>the seabed [2]. However, due to the unique challenges posed<br>by underwater operations, cleanup efforts often rel for Efficient Marine<br>etection<br>Zhang, Ruiqing Shan<br>with the weight of biofouling, can lose buoyancy and sink to<br>the seabed [2]. However, due to the unique challenges posed<br>by underwater operations, cleanup efforts often rel **CECTION**<br>
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Zhang, Ruiqing Shan<br>with the weight of biofouling, can lose buoyancy and sink to<br>the seabed [2]. However, due to the unique challenges posed<br>by underwater operations, cleanup efforts often rely on<br>manual methods, which ine Zhang, Ruiqing Shan<br>with the weight of biofouling, can lose buoyancy and sink to<br>the seabed [2]. However, due to the unique challenges posed<br>by underwater operations, cleanup efforts often rely on<br>manual methods, which ine with the weight of biofouling, can lose buoyancy and sink to<br>the seabed [2]. However, due to the unique challenges posed<br>by underwater operations, cleanup efforts often rely on<br>manual methods, which inevitably result in hi with the weight of biofouling, can lose buoyancy and sink to<br>the seabed [2]. However, due to the unique challenges posed<br>by underwater operations, cleanup efforts often rely on<br>manual methods, which inevitably result in hi with the weight of biofouling, can lose buoyancy and sink to<br>the seabed [2]. However, due to the unique challenges posed<br>by underwater operations, cleanup efforts often rely on<br>manual methods, which inevitably result in hi the seabed [2]. However, due to the unique challenges posed<br>by underwater operations, cleanup efforts often rely on<br>manual methods, which inevitably result in higher costs and<br>certain risks. Consequently, the cleaning work by underwater operations, cleanup efforts often rely on<br>manual methods, which inevitably result in higher costs and<br>certain risks. Consequently, the cleaning work of underwater<br>trash still faces significant challenges.<br>Sin manual methods, which inevitably result in higher costs and<br>certain risks. Consequently, the cleaning work of underwater<br>trash still faces significant challenges.<br>Since the construction of the CNN network AlexNet by<br>Hinton certain risks. Consequently, the cleaning work of underwater<br>trash still faces significant challenges.<br>Since the construction of the CNN network AlexNet by<br>Hinton in 2012 [3], deep learning has made an entrance into<br>an era trash still faces significant challenges.<br>
Since the construction of the CNN network AlexNet by<br>
Hinton in 2012 [3], deep learning has made an entrance into<br>
an era of rapid expansion. A highly influential event<br>
occurred Since the construction of the CNN network AlexNet by<br>Hinton in 2012 [3], deep learning has made an entrance into<br>an era of rapid expansion. A highly influential event<br>occurred in 2016 when AlphaGo, utilizing deep learning<br> Hinton in 2012 [3], deep learning has made an entrance into<br>an era of rapid expansion. A highly influential event<br>occurred in 2016 when AlphaGo, utilizing deep learning<br>techniques, defeated the world champion in the game o an era of rapid expansion. A highly influential event<br>occurred in 2016 when AlphaGo, utilizing deep learning<br>techniques, defeated the world champion in the game of Go<br>[4]. This brought artificial intelligence into the publ occurred in 2016 when AlphaGo, utilizing deep learning<br>techniques, defeated the world champion in the game of Go<br>[4]. This brought artificial intelligence into the public<br>spotlight and sparked global attention and extensiv thriques, defeated the world champion in the game of Go<br>|. This brought artificial intelligence into the public<br>otlight and sparked global attention and extensive<br>ccussions on deep learning. Due to its advantages in<br>aptabi [4]. This brought artificial intelligence into the public spotlight and sparked global attention and extensive discussions on deep learning. Due to its advantages in adaptability, data-driven nature, scalability, and high spotlight and sparked global attention and extensive discussions on deep learning. Due to its advantages in adaptability, data-driven nature, scalability, and high precision [5], deep learning has been proven to be a highl discussions on deep learning. Due to its advantages in<br>adaptability, data-driven nature, scalability, and high<br>precision [5], deep learning has been proven to be a highly<br>effective method for replacing traditional manual l

This research indicates that the proposed<br>
inversume method can develop more efficient underwater were model<br>
inversume method can develop more effection models for embedded devices or mobile<br>
and an efficient method for u adaptability, data-driven nature, scalability, and high<br>precision [5], deep learning has been proven to be a highly<br>effective method for replacing traditional manual labor in<br>numerous fields. With the increasing maturity o precision [5], deep learning has been proven to be a highly<br>effective method for replacing traditional manual labor in<br>numerous fields. With the increasing maturity of<br>autonomous underwater vehicles in the hardware domain, effective method for replacing traditional manual labor in<br>numerous fields. With the increasing maturity of<br>autonomous underwater vehicles in the hardware domain,<br>using autonomous intelligent machines to replace manual<br>lab numerous fields. With the increasing maturity of autonomous underwater vehicles in the hardware domain, using autonomous intelligent machines to replace manual labor for marine debris detection and cleaning has become an e autonomous underwater vehicles in the hardware domain, using autonomous intelligent machines to replace manual labor for marine debris detection and cleaning has become an efficient method for underwater garbage removal. A using autonomous intelligent machines to replace manual<br>labor for marine debris detection and cleaning has become<br>an efficient method for underwater garbage removal.<br>An excellent detection algorithm can provide real-time<br>a labor for marine debris detection and cleaning has become<br>an efficient method for underwater garbage removal.<br>An excellent detection algorithm can provide real-time<br>and reliable target information to machines, assisting th an efficient method for underwater garbage removal.<br>
An excellent detection algorithm can provide real-time<br>
and reliable target information to machines, assisting them<br>
in completing garbage recognition and detection task An excellent detection algorithm can provide real-time<br>and reliable target information to machines, assisting them<br>in completing garbage recognition and detection tasks. This<br>paper proposes optimization and improvement re and reliable target information to machines, assisting them<br>in completing garbage recognition and detection tasks. This<br>paper proposes optimization and improvement research<br>based on YOLOv5s target detection algorithm, aim in completing garbage recognition and detection tasks. This<br>paper proposes optimization and improvement research<br>based on YOLOv5s target detection algorithm, aiming to<br>solve the limitations of hardware computing power and paper proposes optimization and improvement research<br>based on YOLOv5s target detection algorithm, aiming to<br>solve the limitations of hardware computing power and<br>real-time detection in actual mobile device applications.<br>Th based on YOLOv5s target detection algorithm, aiming to<br>solve the limitations of hardware computing power and<br>real-time detection in actual mobile device applications.<br>Through lightweight and high-precision optimization, it solve the limitations of hardware computing power and<br>real-time detection in actual mobile device applications.<br>Through lightweight and high-precision optimization, it<br>provides technical support for accurate and fast marin real-time detection in actual mobile device applications.<br>Through lightweight and high-precision optimization, it<br>provides technical support for accurate and fast marine<br>debris cleanup. This article's subsequent sections a support for accurate and fast marine<br>
his article's subsequent sections are<br>
ws: Section Two outlines the current<br>
water target detection. Section Three<br>
he YOLOv5s algorithm, focusing on its<br>
ks, FasterNet and Ghost Convo bris cleanup. This article's subsequent sections are ganized as follows: Section Two outlines the current earerch on underwater target detection. Section Three effly introduces the YOLOv5s algorithm, focusing on its htweig organized as follows: Section Two outlines the current<br>research on underwater target detection. Section Three<br>briefly introduces the YOLOv5s algorithm, focusing on its<br>lightweight networks, FasterNet and Ghost Convolution. research on underwater target detection. Section Three<br>briefly introduces the YOLOv5s algorithm, focusing on its<br>lightweight networks, FasterNet and Ghost Convolution. It<br>also discusses improvements like SE attention and t THE entire world is currently grappling with a growing<br>and serious problem: pollution caused by marine debris.<br>The presence of garbage in underwater environments not<br>anticological current for presence of the factomeration,

briefly introduces the YOLOv5s algorithm, focusing on its<br>lightweight networks, FasterNet and Ghost Convolution. It<br>also discusses improvements like SE attention and the<br>modified *EloU* loss function. Section Four details lightweight networks, FasterNet and Ghost Convolution. It<br>also discusses improvements like SE attention and the<br>modified *EloU* loss function. Section Four details the<br>experimental results and provides an investigation of also discusses improvements like SE attention and the<br>modified *EloU* loss function. Section Four details the<br>experimental results and provides an investigation of the<br>enhanced algorithm. Lastly, Section Five draws conclus modified *EIoU* loss function. Section Four details the<br>experimental results and provides an investigation of the<br>enhanced algorithm. Lastly, Section Five draws conclusions<br>from the experiments and proposes future enhancem

aszhangxx@163.com).<br>Ruiqing Shan is a Postgraduate Student of School of Computer Science reality is that nearly seventy percent of the waste sinks to<br>
experimental results<br>
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Softw the seabed [1]. Even low-density polymers, when combin<br>Manuscript received Sep 9, 2023; revised Jun 8, 2024.<br>S. C. Li is a Postgraduate Student of School of Computer Science<br>Software Engineering, University of Science and

**Engineering Letters**<br>environments. Still, deep learning has become a hot topic in real-time demands of useful app<br>object detection due to its excellent robustness and effective adoption of big models is l<br>representation o **Engineering Letters**<br>environments. Still, deep learning has become a hot topic in real-time demands of use<br>object detection due to its excellent robustness and effective adoption of big model<br>representation of image detec **Engineering Letters**<br>
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scenes and have the potential to overcome the limitations of<br>
issues. In traditional methods [6].<br>
In order to identify underwater debris, Valdenegro-Toro<br>
ighter enes and have the potential to overcome the limitations of issues. In this study, the ditional methods [6]. YOLOv5 backbone network<br>In order to identify underwater debris, Valdenegro-Toro lighter network. Taking adve<br>Jused Traditional methods [6]. YOLOv5 backbone ne<br>
In order to identify underwater debris, Valdenegro-Toro lighter network. Takir<br>
[7] used a convolutional neural network that had been and computational redeveloped on proactive In order to identify underwater debris, Valdenegro-Toro lighter network. Taking a<br>
[7] used a convolutional neural network that had been and computational requir<br>
developed on proactive sonar imagery, yielding an accuracy [7] used a convolutional neural network that had been and computational requirem<br>developed on proactive sonar imagery, yielding an accuracy lightweightization. Second, in<br>of approximately 80%. However, this approach relied

developed on proactive sonar imagery, yielding an accuracy<br>
of approximately 80%. However, this approach relied on a<br>
use the Ghost module from<br>
simulated dataset created by introducing typical objects<br>
module. Similar fea of approximately 80%. However, this approach relied on a use the Ghost module from Gh<br>
simulated dataset created by introducing typical objects module. Similar feature maps<br>
encountered in marine debris into a water tank a simulated dataset created by introducing typical objects module. Similar feature mencountered in marine debris into a water tank and capturing Ghost module using less ex forward-looking sonar images. While this study showc encountered in marine debris into a water tank and capturing Chost module using less<br>forward-looking sonar images. While this study showcased achieving lightweightizat<br>the effectiveness of CNN and other deep models in SE a forward-looking sonar images. While this study showcased<br>
achieving lightweightization of<br>
the effectiveness of CNN and other deep models in SE attention module with<br>
identifying small-scale marine debris, their suitabilit the effectiveness of CNN and other deep models in SE attention module videntifying small-scale marine debris, their suitability in computational requirements randural marine environments remains uncertain. In 2019, Lin et identifying small-scale marine debris, their suitability in computational required natural marine environments remains uncertain.<br>
In 2019, Lin et al. proposed the ROIMIX image function has replaced are already or occluded natural marine environments remains uncertain. <br>
In 2019, Lin et al. proposed the ROIMIX image<br>
inhance detection accuracy.<br>
In anymentation technique to address the issue of overlapping in faster converger<br>
or occluded un In 2019, Lin et al. proposed the ROIMIX image function has replaced the<br>augmentation technique to address the issue of overlapping resulting in faster contractives the fusion of candidate bounding boxes and the ROI<br>module augmentation technique to address the issue of overlapping resulting in faster converge<br>or occluded underwater biological targets [8]. This method accuracy.<br>utilizes the fusion of candidate bounding boxes and the ROI<br>undle or occluded underwater biological targets [8]. This method<br>utilizes the fusion of candidate bounding boxes and the ROI<br>module to improve the model's detection capabilities. There<br>has been a slight improvement in detection lizes the fusion of candidate bounding boxes and the ROI<br>
olde to improve the model's detection capabilities. There<br>
Soen a slight improvement in detection accuracy for<br>
The soen a slight improvement in detection accuracy module to improve the model's detection capabilities. There<br>
has been a slight improvement in detection accuracy for<br>
different data. However, when it comes to underwater debris<br>
targets, they are typically distributed in has been a slight improvement in detection accuracy for<br>different data. However, when it comes to underwater debris<br>algorithm in 2020, preser<br>targets, they are typically distributed in a more scattered<br>both speed and accur different data. However, when it comes to underwater debris<br>
algorithm in 2020, presenting<br>
targets, they are typically distributed in a more scattered<br>
both speed and accuracy wher<br>
sugnificantly affect the detection of u

targets, they are typically distributed in a more scattered<br>
in the spanificantly affect the detection of underwater debris<br>
significantly affect the detection of underwater debris<br>
significantly percomented the detection manner. Even if some debris targets overlap, it does not<br>
significantly affect the detection of underwater debris.<br>
Moreover, there are already existing data augmentation<br>
incluses that can simulate target overlap. Theref significantly affect the detection of underwater debris.<br>
algorithm is to immediate<br>
Moreover, there are already existing data augmentation<br>
methods that can simulate target overlap. Therefore, in the<br>
context of detection Moreover, there are already existing data augmentation<br>
methods that can simulate target overlap. Therefore, in the<br>
context of detection algorithms, enhancing the detection<br>
for pre-generated candidate<br>
capabilities of ga methods that can simulate target overlap. Therefore, in the network using deep learning<br>context of detection algorithms, enhancing the detection<br>capabilities of garbage targets is more crucial than<br>methods. Specifically, t context of detection algorithms, enhancing the detection for pre-generated candidate leapabilities of garbage targets is more crucial than methods. Specifically, the in addressing the issue of overlap. In 2021, Shi et al. capabilities of garbage targets is more crucial than methods. Specifically, the didressing the issue of overlap.<br>
In 2021, Shi et al. [9] introduced a method that employed with their class probale R-CNN. By implementing a addressing the issue of overlap.<br>
In 2021, Shi et al. [9] introduced a method that emplo<br>
ResNet as the backbone for feature extraction in Fa<br>
R-CNN. By implementing a bidirectional feature pyra<br>
network, they achieved sub In 2021, Shi et al. [9] introduced a method that employed<br>
SNet as the backbone for feature extraction in Faster<br>
CNN. By implementing a bidirectional feature pyramid<br>
using non-maximum sup<br>
twork, they achieved substanti ResNet as the backbone for feature extraction in Faster<br>
R-CNN. By implementing a bidirectional feature pyramid<br>
metwork, they achieved substantial advancements in both<br>
feature extraction and multi-scale feature fusion a R-CNN. By implementing a bidirectional feature pyramid<br>
metwork, they achieved substantial advancements in both<br>
feature extraction and multi-scale feature fusin, leading to a<br>
motable improvement in underwater object det network, they achieved substantial advancements in both<br>feature extraction and multi-scale feature fusin, leading to a<br>motable improvement in underwater object detection and class<br>achieved was only 4.3, which falls short o

feature extraction and multi-scale feature fusin, leading to a<br>
motable improvement in underwater object detection<br>
accuracy to 88.94%. However, the frame per second<br>
up the YOLOV55 network:<br>
achieved was only 4.3, which notable improvement in underwater object detection garbage detection and class<br>accuracy to 88.94%. However, the frame per second<br>achieved was only 4.3, which falls short of meeting the YOLOv5s networ<br>cal-time detection re accuracy to 88.94%. However, the frame per second<br>
accuracy to as only 4.3, which falls short of meeting<br>
real-time detection requirements. Therefore, there is a need<br>
for further exploration of lightweight networks and m achieved was only 4.3, which falls short of meeting<br>real-time detection requirements. Therefore, there is a need<br>for further exploration of lightweight networks and model<br>compression techniques to achieve faster and more real-time detection requirements. Therefore, there is a need<br>
for further exploration of lightweight networks and model<br>
compression techniques to achieve faster and more efficient<br>
underwater object detection.<br>
In 2022, for further exploration of lightweight networks and model<br>
compression techniques to achieve faster and more efficient<br>
underwater object detection.<br>
In 2022, Wei et al. [10] introduced an enhanced<br>
architecture based on compression techniques to achieve faster and more efficient<br>
underwater object detection.<br>
In 2022, Wei et al. [10] introduced an enhanced<br>
segmentation. They employed deeper contraction and<br>
expansion pathways to achieve underwater object detection.<br>
In 2022, Wei et al. [10] introduced an enhanced<br>
architecture based on U-Net for underwater image semantic<br>
expendition, resulting in improved detection accuracy and<br>
speed. However, it shoul In 2022, Wei et al. [10] introduced an enhanced<br>
architecture based on U-Net for underwater image semantic<br>
expansion pathways to achieve end-to-end image semantic<br>
expansion pathways to achieve end-to-end image semantic<br> architecture based on U-Net for underwater image semantic<br>segmentation. They employed deeper contraction and<br>expansion pathways to achieve end-to-end image semantic<br>segmentation, resulting in improved detection accuracy an EXERCT THE SURFALL THE SURFALL THE SURFALL THE SURFALL THE SURFACT ON THE SURFACT SURFACT IS SURFACT THE SURFACT THE SURFACT THE SURFACT ON THE SURFACT ON THE SURFACT ON THE DETERMIND THE SURFACT ON THE SURFACT ON THE SUR expansion pathways to achieve end-to-end image semantic<br>
segmentation, resulting in improved detection accuracy and<br>
for underwater debris semantic segmentation in their parameter debris semantic segmentation in their exp Example the model action active algorithms the distantice algorithms typically produce a<br>
the median of the state of the state of only 410<br>
training image enhancement, along with over 50 images after undergoing<br>
ting the speed. However, it should be noted that the dataset created<br>for underwater debris semantic segmentation in their<br>experiments was relatively small. It consisted of only 410<br>image enhancement, along with over 50 images afte

**Example 18 Exercise 2018**<br>The demands of useful applications. Additionally, the<br>adoption of big models is hampered by the limited<br>processing and storage power of mobile devices.<br>Lightweight networks were established to re **Example 18 Exercise 15 Separation**<br> **Example 18 Separation**<br> **Example 1 g Letters**<br>
real-time demands of useful applications. Additionally, the<br>
adoption of big models is hampered by the limited<br>
processing and storage power of mobile devices.<br>
Lightweight networks were established to resolve **Exercise 15 Exercise 15 Exercise 15 Exercise 15 Exercise 16 Exercise 16 Exercise 16 Exercise 2016 Consider the state of mobile devices.**<br>Lightweight networks were established to resolve these issues. In this study, the fi **Example 18 Exercise 15 and Solution** and sof useful applications. Additionally, the adoption of big models is hampered by the limited processing and storage power of mobile devices. Lightweight networks were established t **g Letters**<br>real-time demands of useful applications. Additionally, the<br>adoption of big models is hampered by the limited<br>processing and storage power of mobile devices.<br>Lightweight networks were established to resolve the **g Letters**<br>
real-time demands of useful applications. Additionally, the<br>
adoption of big models is hampered by the limited<br>
processing and storage power of mobile devices.<br>
Lightweight networks were established to resolve **g Letters**<br>
real-time demands of useful applications. Additionally, the<br>
adoption of big models is hampered by the limited<br>
processing and storage power of mobile devices.<br>
Lightweight networks were established to resolve **real-time demands of useful applications.** Additionally, the adoption of big models is hampered by the limited processing and storage power of mobile devices. Lightweight networks were established to resolve these issues. real-time demands of useful applications. Additionally, the<br>adoption of big models is hampered by the limited<br>processing and storage power of mobile devices.<br>Lightweight networks were established to resolve these<br>issues. I real-time demands of useful applications. Additionally, the adoption of big models is hampered by the limited processing and storage power of mobile devices. Lightweight networks were established to resolve these issues. I real-time demands of useful applications. Additionally, the adoption of big models is hampered by the limited processing and storage power of mobile devices. Lightweight networks were established to resolve these issues. I real-time demands of useful applications. Additionally, the adoption of big models is hampered by the limited processing and storage power of mobile devices. Lightweight networks were established to resolve these issues. I adoption of big models is hampered by the limited<br>processing and storage power of mobile devices.<br>Lightweight networks were established to resolve these<br>issues. In this study, the first step is to switch out the<br>YOLOv5 bac processing and storage power of mobile devices.<br>Lightweight networks were established to resolve these<br>issues. In this study, the first step is to switch out the<br>YOLOv5 backbone network's C3 module with FasterNet, a<br>lighte Lightweight networks were established to resolve these issues. In this study, the first step is to switch out the YOLOv5 backbone network's C3 module with FasterNet, a lighter network. Taking advantage of its lower paramet issues. In this study, the first step is to switch out the YOLOv5 backbone network's C3 module with FasterNet, a lighter network. Taking advantage of its lower parameter and computational requirements to achieve preliminar YOLOv5 backbone network's C3 module with FasterNet, a<br>lighter network. Taking advantage of its lower parameter<br>and computational requirements to achieve preliminary<br>lightweightization. Second, in the feature fusion section accuracy. tion. Second, in the feature fusion section, we<br>module from GhostNet in place of the Conv<br>lar feature maps may be produced with the<br>tweightization of YOLOv5s. We embed the<br>module with fewer parameters and<br>requirements in t e the Ghost module from GhostNet in place of the Conv<br>dule. Similar feature maps may be produced with the<br>nost module using less expensive linear methods, further<br>hieving lightweightization of YOLOv5s. We embed the<br>latenti module. Similar feature maps may be produced with the<br>Ghost module using less expensive linear methods, further<br>achieving lightweightization of YOLOv5s. We embed the<br>SE attention module with fewer parameters and<br>computatio Ghost module using less expensive linear methods, further achieving lightweightization of YOLOv5s. We embed the SE attention module with fewer parameters and computational requirements in the improved network to enhance de

achieving lightweightization of YOLOv5s. We embed the<br>SE attention module with fewer parameters and<br>computational requirements in the improved network to<br>enhance detection accuracy. Ultimately, the *EloU* loss<br>function has SE attention module with tewer parameters and<br>computational requirements in the improved network to<br>enhance detection accuracy. Ultimately, the *EloU* loss<br>function has replaced the bounding box regression loss,<br>resulting computational requirements in the improved network to<br>enhance detection accuracy. Ultimately, the *EloU* loss<br>function has replaced the bounding box regression loss,<br>resulting in faster convergence and higher regression<br>ac enhance detection accuracy. Ultimately, the *EloU* loss<br>function has replaced the bounding box regression loss,<br>resulting in faster convergence and higher regression loss,<br>resulting in faster convergence and higher regress function has replaced the bounding box regression loss,<br>resulting in faster convergence and higher regression<br>accuracy.<br>III. NETWORK ARCHITECTURE<br>Glenn Jocher introduced the YOLOv5 object detection<br>algorithm in 2020, prese resulting in faster convergence and higher regression<br>accuracy.<br>
III. NETWORK ARCHITECTURE<br>
Glenn Jocher introduced the YOLOv5 object detection<br>
algorithm in 2020, presenting significant improvements in<br>
both speed and acc accuracy.<br>
III. NETWORK ARCHITECTURE<br>
Glenn Jocher introduced the YOLOv5 object detection<br>
algorithm in 2020, presenting significant improvements in<br>
both speed and accuracy when compared to its predecessors<br>
within the YO III. NETWORK ARCHITECTURE<br>
Glenn Jocher introduced the YOLOv5 object detection<br>
algorithm in 2020, presenting significant improvements in<br>
both speed and accuracy when compared to its predecessors<br>
within the YOLO series. III. NETWORK ARCHITECTURE<br>
Glenn Jocher introduced the YOLOv5 object detection<br>
algorithm in 2020, presenting significant improvements in<br>
both speed and accuracy when compared to its predecessors<br>
within the YOLO series. Glenn Jocher introduced the YOLOv5 object detection<br>algorithm in 2020, presenting significant improvements in<br>both speed and accuracy when compared to its predecessors<br>within the YOLO series. The main idea behind the<br>algor algorithm in 2020, presenting significant improvement<br>both speed and accuracy when compared to its predece<br>within the YOLO series. The main idea behind<br>algorithm is to immediately perform item detection<br>classification on a th speed and accuracy when compared to its predecessors<br>thin the YOLO series. The main idea behind the<br>gorithm is to immediately perform item detection and<br>ssification on an image by feeding it into a neural<br>twork using de within the YOLO series. The main idea behind the algorithm is to immediately perform item detection and classification on an image by feeding it into a neural network using deep learning techniques, without the need for pr algorithm is to immediately perform item detection and<br>classification on an image by feeding it into a neural<br>network using deep learning techniques, without the need<br>for pre-generated candidate bounding boxes as in tradit classification on an image by feeding it into a neural<br>network using deep learning techniques, without the need<br>for pre-generated candidate bounding boxes as in traditional<br>methods. Specifically, the input image is divided

1.



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**Engineering Letters**<br>In the first part, input techniques such as mosaic data This modification seeks to in<br>gmentation, adaptive image scaling, and automatic by maintaining the network<br>leulation of optimal anchor box value **Engineering Letters**<br>
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In the first part, input techniques such as mosaic data This modification seeks to<br>
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In the first part, input techniques such as mosaic data This modification seeks to<br>
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In the first part, input techniques such as mosaic data This modification seeks to in<br>
augmentation, adaptive image scaling, and automatic by maintaining the network's<br>
calculation of optimal anchor In the first part, input techniques such as mosaic data This modification seeks to in<br>augmentation, adaptive image scaling, and automatic by maintaining the network<br>calculation of optimal anchor box values are employed. I In the first part, input techniques such as mosaic data This modification seeks to importantion, adaptive image scaling, and automatic by maintaining the network's calculation of optimal anchor box values are employed. In In the first part, input techniques such as mosaic data This modification seeks to im<br>augmentation, adaptive image scaling, and automatic by maintaining the network's<br>calculation of optimal anchor box values are employed. augmentation, adaptive image scaling, and automatic by maintaining the networcal<br>culuation of optimal anchor box values are employed. In module's computational com<br>the second part, Backbone, the main layers consist of Focu calculation of optimal anchor box values are employed. In module's computational con<br>the second part, Backbone, the main layers consist of Focus, FasterNet is a brand new<br>CBS (Conv+Batch Normalization+SiLU), C3, SPP, and the second part, Backbone, the main layers consist of Focus, FasterNet is a brand new neu<br>
CBS (Conv+Batch Normalization+SiLU), C3, SPP, and by Chen et al. in 2023. It surpas<br>
other modules, which are in charge of extract CBS (Conv+Batch Normalization+SiLU), C3, SPP, and by Chen et al. in 2023. It<br>other modules, which are in charge of extracting features speeds on devices by a 1<br>from the input images. A Feature Pyramid Network (FPN) accura other modules, which are in charge of extracting features speeds on devices by a<br>from the input images. A Feature Pyramid Network (FPN) accuracy of different vi<br>and a Path Aggregation Network (PAN) form the neck of the exi from the input images. A Feature Pyramid Network (FPN) accuracy of different visual task<br>and a Path Aggregation Network (PAN) form the neck of the existing operators, especially<br>YOLOv5s, generating a feature pyramid that and a Path Aggregation Network (PAN) form the neck of the existing operators, especial CMCOLOV5s, generating a feature pyramid that enhances the DWConv-FLOPS. The resultions of neck network features. The bounding box that YOLOv5s, generating a feature pyramid that enhances the DWConv-FLOPS. The resulting of neck network features. The bounding box that the operators' frequent regression loss function in the prediction sceicion is the  $CloU$  fusing of neck network features. The bounding box<br>that the operators' frequent<br>regression loss function in the prediction section is the  $CloU$ <br>during depthwise convolution<br>loss. This section will introduce our optimizatio regression loss function in the prediction section is the *CloU* during depthwise convolution,<br>loss. This section will introduce our optimization work on poor FLOPS. In order to redu<br>YOLOv5s' original backbone network is c loss. This section will introduce our optimization work on poor FLOPS. In order to reduction to the great similarity of several end memory accesses while YOLOv5s' original backbone network is capable of strong characterist YOLOv5s in detail, focusing on four parts. (a) Although the and memory accesses v<br>
YOLOv5s' original backbone network is capable of strong characteristics more efficien<br>
feature extraction, the great similarity of several YOLOv5s' original backbone network is capable of strong characteristics more efficiently,<br>feature extraction, the great similarity of several (PConv) is presented. Based on<br>convolutions leads to a lot of duplication in fea feature extraction, the great similarity of several (PConv) is presented. B<br>convolutions leads to a lot of duplication in feature maps. To proposed. This innove<br>reduce the model parameters, the YOLOv5s backbone running sp convolutions leads to a lot of duplication in feature maps. To proposed. This innovation-<br>reduce the model parameters, the YOLOv5s backbone running speed of the replaces the original C3 module with a lightweight accuracy. reduce the model parameters, the YOLOv5s backbone running speed of the network replaces the original C3 module with a lightweight accuracy.<br>C3-Faster module, achieving an initial lightweight model. (b) Fig. 2 shows the gen **CIOU CONTEX ENTER CONTER CONTER CONTER CONTEX CONTEX CONDIDENT CONDIDENT SCALL THE CONDIDE in the feature fluid in the feature of the CHOM CONTER CONTE** C3-Faster module, achieving an initial lightweight model. (b) Fig. 2 shows the get Introduce the Ghost module in GhostNet to replace the Conventional convolution module is that it can generate similar feature only the mod Introduce the Ghost module in GhostNet to repl<br>module in the feature fusion part. The feature<br>module is that it can generate similar featur<br>low-cost linear operations. With this arch<br>model's computational load is further d Faster Network<br> *A. FasterNet Network* and the arguments. With this architecture<br> *A.* FasterNetwork is further made lighter. (c) describes a<br> *A.* further made lighter. (c) describes a<br> *A.* Fewterntion mechanisms are use Solutional load is further decreased, and the contiguous channels are regard<br>
Work is further made lighter. (c) describes adding feature map for calculation whe<br>
rameters and calculations to the network. Fewer SE memory ac

First of lightweight backbones. (d) For faster training sacrificing generality. Memory<br>
convergence and better positioning accuracy, change the redundancies are decreased wi<br>
CloU loss to the EloU loss. After the above adj CAL UNIVER THE CONTINUTE CONTINUTE IS the EVALUATE CONTROLL CONTINUTE CONTINUITY CONTINUITY CONTROLL AT A SURVEY CONTROLL AND MOVED THE COMPONENT CONTROLL AND MANUTE COMPONENT CONTROLLY THE COMPONENT CONTROLLY THE COMPONEN CIoU loss to the EIoU loss. After the above adjustments, the module. The FasterNet Block complex scenes.<br>
and accuracy when handling each block consists of two Con<br>
complex scenes. and accuracy when handling each block co model shows higher robustness and accuracy when handling<br>
each block consists of two<br>
complex scenes.<br>
A. FasterNet Network<br>
The C3 module is an important component in the TeaterNet Block, which a shortcut to reuse<br>
The C

**Example 18 Exercise 19 Exercise 20 Exercise 19 Exerci Example 18 Exercise 19 Exerci** 

g Letters<br>This modification seeks to improve the model's efficiency<br>by maintaining the network's depth while reducing the<br>module's computational complexity and parameter count.<br>FasterNet is a brand new neural network famil Letters<br>
is modification seeks to improve the model's efficiency<br>
maintaining the network's depth while reducing the<br>
pdule's computational complexity and parameter count.<br>
FasterNet is a brand new neural network family pr **Example 15**<br>This modification seeks to improve the model's efficiency<br>by maintaining the network's depth while reducing the<br>module's computational complexity and parameter count.<br>FasterNet is a brand new neural network fa **Species 12**<br> **Specification**<br> **Specification**<br> **Specification**<br> **Specifications Examplement is a brand new neural network family proposed**<br> **by Chen et al. in 2023. It surpasses rival networks' operating**<br> **speeds on de Example 18**<br>
This modification seeks to improve the model's efficiency<br>
by maintaining the network's depth while reducing the<br>
module's computational complexity and parameter count.<br>
FasterNet is a brand new neural networ **This modification seeks to improve the model's efficiency**<br>by maintaining the network's depth while reducing the<br>module's computational complexity and parameter count.<br>FasterNet is a brand new neural network family propos **This modification seeks to improve the model's efficiency**<br>by maintaining the network's depth while reducing the<br>module's computational complexity and parameter count.<br>FasterNet is a brand new neural network family propos This modification seeks to improve the model's efficiency<br>by maintaining the network's depth while reducing the<br>module's computational complexity and parameter count.<br>FasterNet is a brand new neural network family proposed This modification seeks to improve the model's efficiency<br>by maintaining the network's depth while reducing the<br>module's computational complexity and parameter count.<br>FasterNet is a brand new neural network family proposed This modification seeks to improve the model's efficiency<br>by maintaining the network's depth while reducing the<br>module's computational complexity and parameter count.<br>FasterNet is a brand new neural network family proposed This modification seeks to improve the model's efficiency<br>by maintaining the network's depth while reducing the<br>module's computational complexity and parameter count.<br>FasterNet is a brand new neural network family proposed by maintaining the network's depth while reducing the module's computational complexity and parameter count.<br>
FasterNet is a brand new neural network family proposed<br>
by Chen et al. in 2023. It surpasses rival networks' op module's computational complexity and parameter count.<br>
FasterNet is a brand new neural network family proposed<br>
by Chen et al. in 2023. It surpasses rival networks' operating<br>
speeds on devices by a large margin while mai FasterNet is a brand new neural network family proposed<br>by Chen et al. in 2023. It surpasses rival networks' operating<br>speeds on devices by a large margin while maintaining the<br>accuracy of different visual tasks. The netwo by Chen et al. in 2023. It surpasses rival networks' operating<br>speeds on devices by a large margin while maintaining the<br>accuracy of different visual tasks. The network re-examines<br>the existing operators, especially the co accuracy. curacy of different visual tasks. The network re-examines<br>e existing operators, especially the computational speed of<br>MConv-FLOPS. The results of the investigation showed<br>the operators' frequent memory access, especially<br>r the existing operators, especially the computational speed of DWConv-FLOPS. The results of the investigation showed that the operators' frequent memory access, especially during depthwise convolution, is the main reason fo DWConv-FLOPS. The results of the investigation showed<br>that the operators' frequent memory access, especially<br>during depthwise convolution, is the main reason for the<br>poor FLOPS. In order to reduce unnecessary calculations<br> that the operators' frequent memory access, especially<br>during depthwise convolution, is the main reason for the<br>poor FLOPS. In order to reduce unnecessary calculations<br>and memory accesses while also extracting spatial<br>char

metwork is further made lighter. (c) describes adding feature map for calculation where<br>arameters and calculations to the network. Fewer SE memory access. It is considered<br>attention mechanisms are used to enhance the extra parameters and calculations to the network. Fewer SE memory access. It is considered attention mechanisms are used to enhance the extraction feature maps' channel course<br>frect of lightweight backbones. (d) For faster trai attention mechanisms are used to enhance the extraction<br>
effect of lightweight backbones. (d) For faster training<br>
exactioning secrificing generality. Memory<br>
convergence and better positioning accuracy, change the<br>
comple during depthwise convolution, is the main reason for the<br>poor FLOPS. In order to reduce unnecessary calculations<br>and memory accesses while also extracting spatial<br>characteristics more efficiently, a unique partial convolut poor FLOPS. In order to reduce unnecessary calculations<br>and memory accesses while also extracting spatial<br>characteristics more efficiently, a unique partial convolution<br>(PConv) is presented. Based on PConv, FasterNet is fu and memory accesses while also extracting spatial<br>characteristics more efficiently, a unique partial convolution<br>(PConv) is presented. Based on PConv, FasterNet is further<br>proposed. This innovation significantly improves t characteristics more efficiently, a unique partial convolution (PConv) is presented. Based on PConv, FasterNet is further proposed. This innovation significantly improves the running speed of the network while maintaining (PConv) is presented. Based on PConv, FasterNet is further<br>proposed. This innovation significantly improves the<br>running speed of the network while maintaining its<br>accuracy.<br>Fig. 2 shows the general design of FasterNet. The proposed. This innovation significantly improves the running speed of the network while maintaining its accuracy.<br>
Fig. 2 shows the general design of FasterNet. The network shows a simple PConv module that simply applies a running speed of the network while maintaining its accuracy.<br>Fig. 2 shows the general design of FasterNet. The<br>network shows a simple PConv module that simply applies a<br>conventional convolution operation to a selected numb accuracy.<br>
Fig. 2 shows the general design of FasterNet. The<br>
network shows a simple PConv module that simply applies a<br>
conventional convolution operation to a selected number of<br>
input channels, keeping the remaining cha Fig. 2 shows the general design of FasterNet. The<br>network shows a simple PConv module that simply applies a<br>conventional convolution operation to a selected number of<br>input channels, keeping the remaining channels unchange network shows a simple PConv module that simply applies a<br>conventional convolution operation to a selected number of<br>input channels, keeping the remaining channels unchanged,<br>in order to extract spatial information. The fi conventional convolution operation to a selected number of<br>input channels, keeping the remaining channels unchanged,<br>in order to extract spatial information. The first or final<br>contiguous channels are regarded as indicativ input channels, keeping the remaining channels unchanged,<br>in order to extract spatial information. The first or final<br>contiguous channels are regarded as indicative of the full<br>feature map for calculation when using sequen in order to extract spatial information. The first or final<br>contiguous channels are regarded as indicative of the full<br>feature map for calculation when using sequential or regular<br>memory access. It is considered that the i contiguous channels are regarded as indicative of the full<br>feature map for calculation when using sequential or regular<br>memory access. It is considered that the input and output<br>feature maps' channel counts are the same wi feature map for calculation when using sequential or regular<br>memory access. It is considered that the input and output<br>feature maps' channel counts are the same without<br>sacrificing generality. Memory accesses and computati memory access. It is considered that the input and output<br>feature maps' channel counts are the same without<br>sacrificing generality. Memory accesses and computational<br>redundancies are decreased with the addition of the PCon feature maps' channel counts are the same without<br>sacrificing generality. Memory accesses and computational<br>redundancies are decreased with the addition of the PConv<br>module. The FasterNet Block is suggested using PConv;<br>ea sacrificing generality. Memory accesses and computational<br>redundancies are decreased with the addition of the PConv<br>module. The FasterNet Block is suggested using PConv;<br>each block consists of two Conv 1x1 layers after a P redundancies are decreased with the addition of the PConv<br>module. The FasterNet Block is suggested using PConv;<br>each block consists of two Conv 1x1 layers after a PConv<br>layer. Together, they are shown as inverted residual module. The FasterNet Block is suggested using PConv;<br>each block consists of two Conv 1x1 layers after a PConv<br>layer. Together, they are shown as inverted residual blocks,<br>with a shortcut to reuse input features and an in



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Engineering Letters<br>
FasterNet blocks are positioned in the final two stages.<br>
Accordingly, more computations are allocated to the last<br>
two stages.<br>
With the help of the Fasternet block structure, a<br>
C3 foster module is p

FasterNet blocks are positioned in the 1<br>Accordingly, more computations are allo<br>two stages.<br>With the help of the Fasternet blo<br>C3-faster module is proposed. In con-<br>previous C3 module, the new C3-fast Engineering Letters<br>
FasterNet blocks are positioned in the final two stages.<br>
Accordingly, more computations are allocated to the last<br>
two stages.<br>
With the help of the Fasternet block structure, a<br>
C3-faster module is p Engineering Letters<br>
FasterNet blocks are positioned in the final two stages.<br>
Accordingly, more computations are allocated to the last<br>
two stages.<br>
With the help of the Fasternet block structure, a<br>
C3-faster module is p **Engineering Letters**<br>
FasterNet blocks are positioned in the final two stages.<br>
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two stages.<br>
With the help of the Fasternet block structure, a<br>
C3-faster module is **Engineering Letters**<br>
FasterNet blocks are positioned in the final two stages.<br>
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two stages.<br>
With the help of the Fasternet block structure, a<br>
C3-faster module is **Engineering Letters**<br>
FasterNet blocks are positioned in the final two stages.<br>
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With the help of the Fasternet block structure, a<br>
C3-faster module is Engineering Letters<br>
FasterNet blocks are positioned in the final two stages.<br>
Accordingly, more computations are allocated to the last<br>
two stages.<br>
With the help of the Fasternet block structure, a<br>
C3-faster module is p FasterNet blocks are positioned in the final two stages.<br>Accordingly, more computations are allocated to the last<br>two stages.<br>With the help of the Fasternet block structure, a<br>C3-faster module is proposed. In comparison to FasterNet blocks are positioned in the final two stages.<br>Accordingly, more computations are allocated to the last<br>two stages.<br>With the help of the Fasternet block structure, a<br>C3-faster module is proposed. In comparison to *B.* GhostNet To further lightweight the algorithm, hostconv from GhostNet is also a lightweight and has fewer parameters in the algorithm provided while maintaining a lightweight model and improves the goal of creating ph With the help of the Fasternet block structure, a<br>
S-faster module is proposed. In comparison to the<br>
evious C3 module, the new C3-faster requires less<br>
mputing power and has fewer parameters. It can reduce<br>
e number of p C3-faster module is proposed. In comparison to the<br>previous C3 module, the new C3-faster requires less<br>computing power and has fewer parameters. It can reduce<br>the number of parameters in the algorithm and the<br>conventional previous C3 module, the new C3-faster requires less<br>
computing power and has fewer parameters. It can reduce<br>
the number of parameters in the algorithm and the<br>
computational load while maintaining good detection<br>
accuracy

computing power and has fewer parameters. It can reduce<br>the number of parameters in the algorithm and the<br>computational load while maintaining good detection<br>accuracy. This achieves the goal of creating a preliminary<br>dight For the number of parameters in the algorithm and the<br>computational load while maintaining good detection<br>accuracy. This achieves the goal of creating a preliminary<br>lightweight model and improves the performance of marine<br> expensive operations computational and while maintaining good detection<br>accuracy. This achieves the goal of creating a preliminary<br>lightweight model and improves the performance of marine<br>debris detection to some extent.<br><br> Examplementation: This achieves the goal of creating a preliminary<br>
lightweight model and improves the performance of marine<br>
debris detection to some extent.<br>
To further lightweight the algorithm, we introduced<br>
Ghostony Example the solution of the Ghost model and improves the performance of marine<br>debris detection to some extent.<br>
To further lightweight the algorithm, we introduced<br>
To further lightweight the algorithm, we introduced<br>
Gh **Examplementation:** a regular convolution and a linear<br>
finite apportion of the feature fusion part.<br>
To further lightweight the algorithm, we introduced<br>
GhostNet is also a lightweight network that transforms the<br>
From eq B. *GhostNet*<br>
To further lightweight the algorithm, we introduced<br>
Ghostconv from GhostNet in the feature fusion part.<br>
GhostNet is also a lightweight network that transforms the<br>
From equations (1) is<br>
heavy convolutiona B. *GhostNet*<br>
To further lightweight the algorithm, we introduced<br>
Ghostconv from GhostNet in the feature fusion part.<br>
GhostNet is also a lightweight network that transforms the<br>
heavy convolutional operations into gene *B. GhostNet*<br>
To further lightweight the algorithm, we introduced<br>
GhostNet in GhostNet in the feature fusion part.<br>
ChostNet is also a lightweight network that transforms the<br>
chostNet is also a lightweight network that To further lightweight the algorithm, we introduced<br>
Ghostconv from GhostNet in the feature fusion part.<br>
GhostNet is also a lightweight network that transforms the<br>
leavy convolutional operations into generating a few<br>
l Ghostonv from GhostNet in the feature fusion part.<br>
GhostNet is also a lightweight network that transforms the<br>
heavy convolutional operations into generating a few<br>
linghly diversified feature maps [14]. Then, it applies GhostNet is also a lightweight network that transforms the<br>heavy convolutional operations into generating a few<br>inclusion in the computational expense of<br>highly diversified feature maps [14]. Then, it applies less times g heavy convolutional operations into generating a few<br>highly diversified feature maps [14]. Then, it applies less<br>expensive operations compared to regular convolutions to<br>transform these feature maps and obtain similar fea Assumming the given input data  $X \in \mathbb{R}^{e \times w \times w}$  represents from the ensire and obtain similar feature also roughly s times<br>nsform these feature maps and obtain similar feature also roughly s times<br>nps. There are two c expensive operations compared to regular convolutions to<br>
transform these feature maps and obtain similar feature also roughly s tim<br>
maps. There are two components to the Ghost model's acceleration and para<br>
implementati transform these feature maps and obtain similar feature<br>
implementation: a regular convolution and a linear convolution and a linear convolution and a linear convolution and a linear the transformation count,<br>
a portion o maps. There are two components to the Ghost module's<br>implementation: a regular convolution and a linear<br>operation with fewer parameters and computations. Firstly,<br>fe<br>operation of the feature maps is obtained through a lim components to the Ghost module's acceleration and parameter egular convolution and a linear the transformation count. Sarameters and computations. Firstly, feature maps generated, the maps is obtained through a limited bu

mplementation: a regular convolution and a linear<br>operation with fewer parameters and computations. Firstly, feature maps is obtained through a limited<br>regular convolution. Then, the obtained feature maps are<br>transformati operation with fewer parameters and computations. Firstly,<br>
a portion of the feature maps is obtained through a limited<br>
reqular convolution count is ofted feature maps are<br>
further expanded by the linear operation to get a portion of the feature maps is obtained through a limited<br>regular convolution. Then, the obtained feature maps are<br>transformation cot<br>further expanded by the linear operation to get more feature<br>along the designated axi regular convolution. Then, the obtained feature maps are<br>
further expanded by the linear operation to get more feature<br>
along the designated axis. Fig. 3 compares regular<br>
along the designated axis. Fig. 3 compares regula further expanded by the linear operation to get more teature<br>
along the designated axis. Fig. 3 compares regular<br>
components between s<br>
along the designated axis. Fig. 3 compares regular<br>
convolution with ghost convolutio maps. Ultimately, the two teature map sets are combined<br>along the designated axis. Fig. 3 compares regular<br>convolution with ghost convolution.<br>Convolution with ghost convolutional<br>and w stand for the height and breadth of along the designated axis. Fig. 3 compares regu<br>convolution with ghost convolution.<br>Assuming the given input data  $X \n\t\in R^{c \times h \times w}$ , where<br>and w stand for the height and breadth of the informati<br>being input, respectively ights h' and widths w', the quantity of convolutional<br>
ters is n, with k as the kernel size, and the linear<br>
msformation has a kernel size of d and a transformation<br>
mechanisms can amplify or<br>
mechanisms can amplify or<br>
m filters is n, with k as the kernel size, and<br>transformation has a kernel size of d and a tra<br>count of s. In the absence of bias terms b, the<br>compression ratio achieved by replacing<br>convolutions with Ghost convolutions can

$$
r_c = \frac{c \cdot n \cdot k \cdot k}{c \cdot k \cdot k \cdot \frac{n}{s} \cdot +(s-1) \cdot d \cdot d \cdot \frac{n}{s}} \approx \frac{c \cdot s}{c+s-1} \approx s \quad (1)
$$
 attention mechanisms such as CBAM,  
Fig. 4 depicts the SE attention mechanism  
It primarily involves two steps: squ

$$
r_s = \frac{c \cdot n \cdot k \cdot k \cdot h' \cdot w'}{c \cdot k \cdot k \cdot \frac{n}{s} \cdot h' \cdot w' + (s-1) \cdot d \cdot d \cdot \frac{n}{s} \cdot h' \cdot w'}
$$
  
= 
$$
\frac{c \cdot k \cdot k}{c \cdot k \cdot k \cdot \frac{1}{s} + d \cdot d \cdot \frac{(s-1)}{s}} \approx \frac{c \cdot s}{c + s - 1} \approx s
$$
  
is retained. In the excitation  
(2) is retained. In the excitation  
introducing non-linear tra  
linked layers pick up on e  
inthroduce non-linearity,



it applies less<br>
intervalses imes greater than that of ord<br>
intervalses implies the computational cost for an equi<br>
similar feature also roughly s times. The<br>
Shost module's acceleration and parameter con<br>
and a linear the Convertible Constrained Controllers and the Controllers of Constructional cost for an equivalent set of parameters is also roughly s times. The benefits of computational acceleration and parameter compression are influence also roughly s times. The benefits of computational acceleration and parameter compression are influenced by the transformation count. Specifically, the more "ghost" feature maps generated, the better the acceleration effe Fig. 3. GhostNet network structure.<br>
Fig. 3. GhostNet network structure.<br>
From equations (1) and (2), it is evident that the<br>
computational expense of Ghost convolution is around s<br>
times greater than that of ordinary conv The Ghost module<br>
The Ghost module<br>
Fig. 3. GhostNet network structure.<br>
From equations (1) and (2), it is evident that the<br>
computational expense of Ghost convolution is around s<br>
times greater than that of ordinary convo Fig. 3. GhostNet network structure.<br>
Fig. 3. GhostNet network structure.<br>
From equations (1) and (2), it is evident that the<br>
computational expense of Ghost convolution is around s<br>
times greater than that of ordinary con (b)The Ghost module<br>
Fig. 3. GhostNet network structure.<br>
From equations (1) and (2), it is evident that the<br>
computational expense of Ghost convolution is around s<br>
times greater than that of ordinary convolution, and th (b)The Ghost module<br>Fig. 3. GhostNet network structure.<br>
From equations (1) and (2), it is evident that the<br>
computational expense of Ghost convolution is around s<br>
times greater than that of ordinary convolution, and the Fig. 3. GhostNet network structure.<br>
From equations (1) and (2), it is evident that the<br>
computational expense of Ghost convolution is around s<br>
times greater than that of ordinary convolution, and the<br>
computational cost From equations (1) and (2), it is evident if<br>omputational expense of Ghost convolution is are<br>mes greater than that of ordinary convolution, a<br>monotational cost for an equivalent set of parames<br>so roughly s times. The ben The attention mechanism is a visual focus mechanism is to quively extract the consideration and parameters is<br>to roughly s times. The benefits of computational<br>celeration and parameter compression are influenced by<br>transfo computational cost for an equivalent set of parameters is<br>also roughly s times. The benefits of computational<br>acceleration and parameter compression are influenced by<br>the transformation count. Specifically, the more "ghost **Example 18 The Schoff Computational acceleration and parameter compression are influenced by** the transformation count. Specifically, the more "ghost" feature maps generated, the better the acceleration effect, but it may

 $\approx \frac{c \cdot s}{s} \approx s$  (1) attention mechanisms such  $\approx \frac{c \cdot s}{s}$ acceleration and parameter compression are influenced by<br>the transformation count. Specifically, the more "ghost"<br>feature maps generated, the better the acceleration effect,<br>but it may lead to a decrease in detection accur The transformation count. Specifically, the more "ghost"<br>feature maps generated, the better the acceleration effect,<br>but it may lead to a decrease in detection accuracy. The<br>transformation count is often set at 1/2 in orde Fracture maps generated, the better the acceleration effect,<br>but it may lead to a decrease in detection accuracy. The<br>transformation count is often set at 1/2 in order to achieve a<br>compromise between speed and precision.<br><br> but it may lead to a decrease in detection accuracy. The<br>transformation count is often set at 1/2 in order to achieve a<br>compromise between speed and precision.<br>C. Squeeze-and-Excitation<br>The attention mechanism is a visual transformation count is often set at  $1/2$  in order to achieve a<br>transformation count is often set at  $1/2$  in order to achieve a<br>compromise between speed and precision.<br> $C. Squareze-and-Excitation$ <br>that simulates the rapid acquisition of *C. Squeeze-and-Excitation*<br> *C. Squeeze-and-Excitation*<br>
The attention mechanism is a visual focus mechanism<br>
that simulates the rapid acquisition of key information and<br>
filtering of irrelevant information in the human b C. *Squeeze-and-Excitation*<br>The attention mechanism is a visual focus mechanism<br>that simulates the rapid acquisition of key information and<br>filtering of irrelevant information in the human brain. It<br>aims to quickly extrac C. *Squeeze-and-Excitation*<br>The attention mechanism is a visual focus mechanism<br>that simulates the rapid acquisition of key information and<br>filtering of irrelevant information in the human brain. It<br>aims to quickly extract C. Squeeze-and-Excitation<br>The attention mechanism is a visual focus mechanism<br>that simulates the rapid acquisition of key information and<br>filtering of irrelevant information in the human brain. It<br>aims to quickly extract t The attention mechanism is a visual focus mechanism<br>that simulates the rapid acquisition of key information and<br>filtering of irrelevant information in the human brain. It<br>aims to quickly extract the crucial features from a that simulates the rapid acquisition of key information and<br>filtering of irrelevant information in the human brain. It<br>aims to quickly extract the crucial features from an image.<br>Attention mechanisms are often employed in filtering of irrelevant information in the human brain. It<br>aims to quickly extract the crucial features from an image.<br>Attention mechanisms are often employed in computer<br>vision to improve neural networks' feature extracti ms to quickly extract the crucial features from an image.<br>
tention mechanisms are often employed in computer<br>
sion to improve neural networks' feature extraction<br>
rformance. By assigning weights to the input, attention<br>
re Attention mechanisms are often employed in computer<br>vision to improve neural networks' feature extraction<br>performance. By assigning weights to the input, attention<br>mechanisms can amplify or emphasize the important<br>feature vision to improve neural networks' feature extraction<br>performance. By assigning weights to the input, attention<br>mechanisms can amplify or emphasize the important<br>feature information in the image, making it a parameterized<br> performance. By assigning weights to the input, attention<br>mechanisms can amplify or emphasize the important<br>feature information in the image, making it a parameterized<br>pooling method. Multiple experiments have shown that t

 $\approx$   $\frac{c \cdot s}{s} \approx s$  linked layers pick up on each cha  $h' \cdot w'$  is issuance. In the exchange is retained. In the excitation step, the global average values introducing non-linear transformations. These completely mechanisms can amplify or emphasize the important<br>feature information in the image, making it a parameterized<br>pooling method. Multiple experiments have shown that the<br>SE attention mechanism, with fewer parameters and<br>compu feature information in the image, making it a parameterized<br>pooling method. Multiple experiments have shown that the<br>SE attention mechanism, with fewer parameters and<br>computational requirements, significantly enhances our<br> pooling method. Multiple experiments have shown that the SE attention mechanism, with fewer parameters and computational requirements, significantly enhances our optimization approach compared to frequently used attention SE attention mechanism, with fewer parameters and<br>computational requirements, significantly enhances our<br>optimization approach compared to frequently used<br>attention mechanisms such as CBAM, CA, and ECA [15].<br>Fig. 4 depicts computational requirements, significantly enhances our<br>optimization approach compared to frequently used<br>attention mechanisms such as CBAM, CA, and ECA [15].<br>Fig. 4 depicts the SE attention mechanism's structure.<br>It primar optimization approach compared to frequently used<br>attention mechanisms such as CBAM, CA, and ECA [15].<br>Fig. 4 depicts the SE attention mechanism's structure.<br>It primarily involves two steps: squeeze and excitation.<br>During attention mechanisms such as CBAM, CA, and ECA [15].<br>Fig. 4 depicts the SE attention mechanism's structure.<br>It primarily involves two steps: squeeze and excitation.<br>During the squeeze, the SE attention mechanism lowers the Fig. 4 depicts the SE attention mechanism's structure.<br>It primarily involves two steps: squeeze and excitation.<br>During the squeeze, the SE attention mechanism lowers the<br>feature maps' dimensionality through worldwide avera



*C*<br> *D*<br>
Fig. 4. Squeeze-and-Exci<br>
ppture complex relationships between channels. To give<br>
degre<br>
ajor feature channels extra weight, the computed channel<br>
eights are finally multiplied by the original feature maps.<br>
mini *Exerce Complex relationships* between channels. To give<br>
Fig. 4. Squeeze-and-Excitation<br>
pigrefeature channels extra weight, the computed channel complicated. It takes interestion<br>
is eights are finally multiplied by the

Fig. 4. Squeeze-and-Excitation<br>major feature channels extra weight, the computed channel complicated. It takes<br>weights are finally multiplied by the original feature maps. union and intersection<br>This enhances the represen Eig. 4. Squeeze-and-Excitation<br>
major feature channels extra weight, the computed channel degree of ambiguity. Also, the<br>
major feature channels extra weight, the computed channel<br>
weights are finally multiplied by the or capture complex relationships between channels. To give degree of ambiguity. Also, the major feature channels extra weight, the computed channel complicated. It takes into accomplicated in the convergence of a modificatio capture complex relationships between channels. To give degree of ambiguity. Also, the major feature channels extra weight, the computed channel complicated. It takes into accouvergents are finally multiplied by the origi major feature channels extra weight, the computed channel<br>major feature channels extra weight, the computed channel<br>weights are finally multiplied by the original feature maps.<br>This enhances the representation capability in equation (3), where values of the Unit of the CloU loss equation (3), where values of the CloU loss equation (3), where values of the CloU loss formulation for the class probability score, the clouding box, and the cen This enhances the representation capability of these bounding box, and the enter portained and suppresses unimportant channels.<br>
Consider the mate of the set of the convergence more precise, there be convergence more prec

$$
CIoU = IoU - (\frac{\rho^2}{C^2} + \alpha v)
$$
 (3) This results in the illogical

$$
v = \frac{4}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h})^2
$$
 descent approach  
(4) descent approach  
complexity sense

$$
\alpha = \frac{v}{v + (1 - IoU)} \qquad \qquad \text{the goals of function is} \qquad \qquad \text{function is} \qquad \qquad \text{function} \qquad \text{function}
$$

Colouring the integral of the expected box and the ground distance of the equation (8), we and the expected by the symbol  $\rho$ , while the diagonal distance of the expected by the symbol  $\rho$ , while the diagonal distance o  $\mathcal{L}IoU = IoU - (\frac{\rho^2}{C^2} + \alpha v)$  (3) This results in the illogical complete the parameters are changed in the parameters. This descen  $\mathcal{L} = \frac{d}{dt} \left( \tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h} \right)^2$  (3) This results in the illogical<br>  $v = \frac{4}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h})^2$  (4) the opposite ways. This complexity, especially in large<br>  $\alpha = \frac{v}{v + (1 - IoU)}$  (5) t  $v = \frac{4}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h})^2$ <br>  $\alpha = \frac{v}{v + (1 - IoU)}$ <br>
Equation (3) shows the crossing point of the square in equation is deployed as the incomplexity, especially in large-<br>
resulting in higher computation fi  $v = \frac{4}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^gt} - \tan^{-1} \frac{w}{h})^2$ <br>
(4) descent approach, the neural<br>
complexity, especially in large<br>
resulting in higher computation<br>
(4) descent approach, the neural<br>
complexity, especially in large<br>
result  $v = \frac{v}{\pi^2} (tan^{-1} \frac{w}{h^{gt}} - tan^{-1} \frac{w}{h})^2$  (4) the opposite ways. To emplexity, especially in la<br>
resulting in higher computation (3) shows the crossing point of the goals of our lightweig<br>
Equation (3) shows the crossing  $\pi^2$   $h^{8}$   $h$   $\cosh{m}$  complexity, especially i<br>  $\alpha = \frac{v}{v + (1 - IoU)}$  (5) the goals of our lightwise in the ground the goals of our lightwise in the ground the properties of the combination of the expected box and the g  $\alpha = \frac{v}{v + (1 - IoU)}$  (5) function (3) shows the crossing point of the combination of the expected box and the ground truth box.<br>The Euclidean separation between the two boxes' centers is denoted by the symbol p, while the d  $\alpha = \frac{v}{v + (1 - IoU)}$  the goals of our lightweighted<br>Equation (3) shows the crossing point of the minimation of the expected box and the ground truth box.<br>
Euclidean separation between the two boxes' centers is<br>
noted by the  $\alpha = \frac{b + (1 - IoU)}{b + (1 - IoU)}$  (5) function is deployed as<br>
Equation (3) shows the crossing point of the<br>
combination of the expected box and the ground truth box.<br>
The Euclidean separation between the two boxes' centers is<br>
d  $v + (1 - IoU)$ <br>
Equation (3) shows the crossing point of the<br>
combination of the expected box and the ground turb box.<br>
The Euclidean separation between the two boxes' centers is<br>
denoted by the symbol c, while the diagonal d

Both The Characterian and the center point. The center of ambiguity. Also, the calculation of  $CIoU$  is more complicated. It takes into account parameters such as the union and intersection ratios, the height and breadth o <sup>11</sup><sup>23</sup><sup>4</sup> H<br>
<sup>12</sup><sup>23</sup><sup>4</sup> H<br>
<sup>23</sup><br>
<br>
degree of ambiguity. Also, the calculation of *CIoU* is more<br>
complicated. It takes into account parameters such as the<br>
union and intersection ratios, the height and breadth of the<br> Excitation<br>degree of ambiguity. Also, the calculation of *CloU* is more<br>complicated. It takes into account parameters such as the<br>union and intersection ratios, the height and breadth of the<br>bounding box, and the center p Excitation<br>degree of ambiguity. Also, the calculation of  $CloU$  is more<br>complicated. It takes into account parameters such as the<br>union and intersection ratios, the height and breadth of the<br>bounding box, and the center po degree of ambiguity. Also, the calculation of  $CloU$  is more complicated. It takes into account parameters such as the union and intersection ratios, the height and breadth of the bounding box, and the center point. The ad degree of ambiguity. Also, the calculation of *CloU* is more complicated. It takes into account parameters such as the union and intersection ratios, the height and breadth of the bounding box, and the center point. The a d-Excitation<br>degree of ambiguity. Also, the calculation of *CloU* is more<br>complicated. It takes into account parameters such as the<br>union and intersection ratios, the height and breadth of the<br>bounding box, and the center

$$
\frac{\partial v}{\partial w} = \frac{8}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h})^* \frac{h}{w^2 + h^2}
$$
 (6)

$$
\frac{\partial v}{\partial h} = -\frac{8}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h})^* \frac{w}{w^2 + h^2}
$$
 (7)

 $\frac{4}{\pi}$  (tan<sup>-1</sup>  $\frac{w^{gt}}{t}$  – tan<sup>-1</sup>  $\frac{w}{t}$ )<sup>2</sup> descent approach, the neural network changes w and h in complexity, especially in large-scale object detection tasks, function is deployed as the new loss function, and its calculation is shown in equation  $(8)$ : Equation (3) shows the crossing point of the ELOU =  $IoU - (\frac{\rho^2}{C^2} + av)$ <br>  $U = \frac{4}{\pi^2} (tan^{-1} \frac{w^{gt}}{h^{gt}} - tan^{-1} \frac{w}{h})^2$ <br>  $= \frac{4}{\pi^2} (tan^{-1} \frac{w^{gt}}{h^{gt}} - tan^{-1} \frac{w}{h})^2$ <br>  $= \frac{v}{\rho + (1 - IoU)}$ <br>
Equation (3) shows the crossing poin mergence. However, when the aspect ratio factor v in<br>  $\frac{\partial D}{\partial u} = \frac{8}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h})^* + \frac{h}{w^2 + h^2}$  (6)<br>  $\frac{\partial v}{\partial h} = -\frac{8}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h})^* + \frac{w}{w^2 + h^2}$  (6)<br>
This results in the *CIoU* calculation equation calculates the gradient for w<br>and h, it will be found that the two have opposing gradient<br>directions., as shown in equations (6) and (7):<br> $\frac{\partial v}{\partial w} = \frac{8}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h$ and h, it will be found that the two have opposing gradient<br>directions., as shown in equations (6) and (7):<br> $\frac{\partial v}{\partial w} = \frac{8}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h}) * \frac{h}{w^2 + h^2}$  (6)<br> $\frac{\partial v}{\partial h} = -\frac{8}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}}$ directions., as shown in equations (6) and (7):<br>  $\frac{\partial v}{\partial w} = \frac{8}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h})^* \frac{h}{w^2 + h^2}$  (6)<br>  $\frac{\partial v}{\partial h} = -\frac{8}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h})^* \frac{w}{w^2 + h^2}$  (7)<br>
This results in the ill  $\frac{\partial v}{\partial w} = \frac{8}{\pi^2} (\tan^2 \frac{w^{gt}}{h^{gt}} - \tan^2 \frac{w}{h})^* \frac{h}{w^2 + h^2}$  (6)<br>  $\frac{\partial v}{\partial h} = -\frac{8}{\pi^2} (\tan^2 \frac{w^{gt}}{h^{gt}} - \tan^2 \frac{w}{h})^* \frac{w}{w^2 + h^2}$  (7)<br>
This results in the illogical consequence that every time<br>
the parameters ar  $\frac{\partial v}{\partial w} = \frac{8}{\pi^2} (\tan^2 \frac{w^{gt}}{h^{gt}} - \tan^2 \frac{w}{h})^* \frac{h}{w^2 + h^2}$  (6)<br>  $\frac{\partial v}{\partial h} = -\frac{8}{\pi^2} (\tan^2 \frac{w^{gt}}{h^{gt}} - \tan^2 \frac{w}{h})^* \frac{w}{w^2 + h^2}$  (7)<br>
This results in the illogical consequence that every time<br>
the parameters ar  $rac{\partial v}{\partial w} = \frac{8}{\pi^2} (\tan^2 \frac{w}{h^{gt}} - \tan^2 \frac{w}{h})^* \frac{n}{w^2 + h^2}$  (6)<br>  $\frac{\partial v}{\partial h} = -\frac{8}{\pi^2} (\tan^2 \frac{w^{gt}}{h^{gt}} - \tan^2 \frac{w}{h})^* \frac{w}{w^2 + h^2}$  (7)<br>
This results in the illogical consequence that every time<br>
the parameters are cha For  $\pi^2$   $h^{st}$   $h$   $w^2 + h^2$  (0)<br>  $\frac{\partial v}{\partial h} = -\frac{8}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h})^* \frac{w}{w^2 + h^2}$  (7)<br>
This results in the illogical consequence that every time<br>
the parameters are changed using the random gradie  $\frac{\partial v}{\partial h} = -\frac{8}{\pi^2} (\tan^{-1} \frac{w^{gt}}{h^{gt}} - \tan^{-1} \frac{w}{h})^* \frac{w}{w^2 + h^2}$  (7)<br>This results in the illogical consequence that every time<br>the parameters are changed using the random gradient<br>descent approach, the neural network Exercise are changed using the random grase<br>
Secent approach, the neural network changes w and<br>
poposite ways. This increases computated<br>
mplexity, especially in large-scale object detection is<br>
sulting in higher computat using the random gradient<br>network changes w and h in<br>increases computational<br>-scale object detection tasks,<br>nal costs. This does not meet<br>model. Therefore, the *EloU*<br>new loss function, and its<br>n (8):<br> $(\frac{\rho_w}{w^c})^2 + (\frac{\rho_h}{$ descent approach, the neural network changes w and h in<br>the opposite ways. This increases computational<br>complexity, especially in large-scale object detection tasks,<br>resulting in higher computational costs. This does not

$$
EIoU = IoU - \left( \left( \frac{\rho}{C} \right)^2 + \left( \frac{\rho_w}{w^c} \right)^2 + \left( \frac{\rho_h}{h^c} \right)^2 \right) \tag{8}
$$

In equation (8),  $w^c$  and  $h^c$  stand for the height and the opposite ways. This increases computational<br>complexity, especially in large-scale object detection tasks,<br>resulting in higher computational costs. This does not meet<br>the goals of our lightweight model. Therefore, the complexity, especially in large-scale object detection tasks,<br>resulting in higher computational costs. This does not meet<br>the goals of our lightweight model. Therefore, the *EloU*<br>function is deployed as the new loss func resulting in higher computational costs. This does not meet<br>the goals of our lightweight model. Therefore, the *EIoU*<br>function is deployed as the new loss function, and its<br>calculation is shown in equation (8):<br> $EIoU = IoU - \left$ the goals of our lightweight model. Therefore, the *EloU*<br>function is deployed as the new loss function, and its<br>calculation is shown in equation (8):<br> $EIoU = IoU - \left( \left( \frac{\rho}{C} \right)^2 + \left( \frac{\rho_w}{w^c} \right)^2 + \left( \frac{\rho_h}{h^c} \right)^2 \right)$  (8)<br> function is deployed as the new loss function, and its<br>calculation is shown in equation (8):<br> $EIoU = IoU - \left( \frac{\rho}{C} \right)^2 + \left( \frac{\rho_w}{w^c} \right)^2 + \left( \frac{\rho_h}{h^c} \right)^2$  (8)<br>In equation (8),  $w^c$  and  $h^c$  stand for the height and<br>breadt



E. *Improved YOLOv5s Network Structure*<br>
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the computational load and complexity of the model. With<br>
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improves inference time without sacrificing perform the computational load and complexity of the model. With<br>
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fewer parameters in the new model, this substitution<br>
feature improves inference time without sacrificing perf fewer parameters in the new model, this substitution<br>
improves inference time without sacrificing performance.<br>
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YOLO improves inference time without sacrificing performance.<br>
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reduce the performance to a certain extent while decreasing<br>
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attention mo computational costs, particularly in mobile devices or<br>
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the resource-constrained environments, aiming to further<br>
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the model's focus on crucial features, improving its<br>
perfor reduce the model's parameter count. Embedding SE<br>
attention modules in the network structure helps enhance<br>
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em is pectrol detection tasks. By increasing the<br>
ing and leveraging key information, the<br>
enhance detection accuracy. Lastly,<br>
loss helps better reflect differences in<br>
mensions of target boxes, improving the<br>
accuracy for o mental is able to enhance detection accuracy. Lastly,<br>
odel is able to enhance detection accuracy. Lastly,<br>
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lizing the EloU loss helps better reflect differences in<br>
position and dimensions of target boxes, improving the<br>
pole!'s prediction accuracy for overlapping objects where the position and dimensions of target boxes, improving the<br>
model's prediction accuracy for overlapping objects or<br>
those with significant size variations in object detection,<br>
thereby enhancing overall detection per

derived from the union of multipled and the state of a model's prediction accuracy for overlapping objects or<br>those with significant size variations in object detection,<br>thereby enhancing overall detection performance. Thi Theorem and the securiton are the set and the control of the control of a model, relations in object detection,<br>thereby enhancing overall detection performance. This<br>process results in an optimized algorithmic model. Fig. The three with a significant size variations in original detection of the comparison of the displays the enhanced YOLOv5s network structure.<br>
Table I lists all of the displays the enhanced YOLOv5s network structure.<br>
IV. E significant virtuous and the control of quality, depth, scene displays the enhanced YOLOv5s network structure.<br>
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is and Experimental Environment<br>
This research employs the Trash-ICRA19 dataset for<br>
This research employs

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dighting vary across the videos. In total, the d Solution Solution Solution Solution Solution Solution Several kinds of marine trash taken in actual settings.<br>
Furthermore, the clarity of the water and the quality of the lighting vary across the videos. In total, the dat e trash taken in actual settings.<br>
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t into training, validation, and test<br>
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TA of marine trash taken in actual settings.<br>
he clarity of the water and the quality of the<br>
across the videos. In total, the dataset<br>
7600 images, encompassing organisms,<br>
ROVs. Prior to conducting experiments, the<br>
were sp





Cuda Cuda10.1<br>
Data Processing Python3.8<br>
DL Framework Pytorch1.7<br>
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**EXECUTE:** The content of the total sum of parameters in a model, which are determined to calculate the model's size. Parameter count refers to the total sum of parameters in a model, which affects both in memory usage an

*Precision* = 
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\frac{TP}{TP + FP}
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 (9) displayed in Fig. 6. Comparat the same environment to evaluate the axis.

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Recall = \frac{TP}{TP + FN}
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 (10) identification models in order  
underwater rubbish detecti

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AP = \int_{0}^{1} P(R) dR \tag{11}
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mAP = \frac{1}{C} \sum_{c \in C} AP(c)
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 (12) single-stage object detection  
classic two-stage object detet

*Precision* =  $\frac{TP}{TP + FP}$  (9) displayed in rig. 6. Con<br>
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identified is represented by True Positives (TP) in the<br>
equations above. The quantity of marine debris sample  $mAP = \frac{1}{C_{\text{eec}}} \Delta P(c)$  (12) single-stage object detection<br>classic two-stage object detection<br>The number of marine debris samples that are accurately<br>dentified is represented by True Positives (TP) in the<br>equations above.  $mAP = \frac{1}{C_{\text{sec}}} AP(c)$  (12) singie-stage object c<br>
classic two-stage object<br>
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equations above. The quantity of marine debris samples<br>
that were missed hy dentified is called False Posit identified is represented by True Positives (TP) in the<br>equations above. The quantity of marine debris samples<br>that were mistakenly identified is called False Positives<br>(FP). The number of samples that are marine debris bu equations above. The quantity of marine debris samples<br>
that were mistakenly identified is called False Positives<br>
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Negatives (FN). For marine debris samples, assessme that were mistakenly identified is called False Positives<br>
(FP). The number of samples that are marine debris but<br>
were missed by the model is represented by False<br>
Negatives (FN). For marine debris samples, assessment<br>
cr (FP). The number of samples that are marine debris but<br>were missed by the model is represented by False SSD<br>Negatives (FN). For marine debris samples, assessment<br>criteria like AP (Average Precision) and mAP (Mean<br>Average P Frace missed by the model is represented by False<br>
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Average Precision) are frequently employed. The number<br>
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Average Precision) are frequently employed. The number<br>
of samples that are marine debris but were missed by the<br>
measures like Average Precision (AP) and Mean Average<br>
m Average Precision) are frequently employed. The number<br>of samples that are marine debris but were missed by the<br>model is represented by False Negatives (FN). Evaluation<br>measures like Average Precision (AP) are frequently e

<sup>2</sup><br>
<sup>C. C. Comparison Results and the enhanced method are<br>
E. C. Comparison Results and Analysis<br>
Therefore, is desirable to have a range of 30FPS or higher to<br>
C. Comparison Results and Analysis<br>
Yolov5's detection resul</sup>

*Fechnique* against the existing mainstream object study. This experiment featured the lightweight network<br>YOLOv5n, the YOLOv5s network with its backbone single-stage object detection technique SSD, and the AP) as assessment criteria. The following formulas can<br>
used to determine these metrics:<br>  $Precision = \frac{TP}{TP + FP}$  (9) displayed in Fig. 6. Correlation models in<br>  $Recall = \frac{TP}{TP + FN}$  (10) identification models in<br>  $AP = \int_{0}^{1} P(R) dR$  (11) be used to determine these metrics:<br>  $Precision = \frac{TP}{TP + FP}$  (9)<br>  $Recall = \frac{TP}{TP + FP}$  (9)<br>  $Recall = \frac{TP}{TP + FN}$  (10)<br>  $Recall = \frac{TP}{TP + FN}$  (10)<br>  $AP = \int_{0}^{1} P(R) dR$  (11)<br>  $= \int_{C}^{1} P(R) dR$  (11)<br>  $= \int_{C}^{1} P(R) dR$  (12)<br>  $= \int_{C}^{1} P(R) dR$  (12)<br>  $= \int_{C}^{1}$ VOLOv5s<br>
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Sand improved algorithm<br>
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Sand improved algorithm<br>
Sand 30 fps. Therefore,<br>
is desirable to have a range of 30FPS or higher to<br>
cilitate real-time garbage detection displayed in Fig. 6. Comparison<br>over the frame rate of real-time cameras is between 24 fps and 30 fps. Therefore,<br>it is desirable to have a range of 30FPS or higher to<br>facilitate real-time garbage detection.<br>C. Comparison The same of YOLOv5s<br>
The same of real-time cameras is between 24 fps and 30 fps. Therefore,<br>
treal-time cameras is between 24 fps and 30 fps. Therefore,<br>
it is desirable to have a range of 30FPS or higher to<br>
facilitate re ov5s and improved algorithm<br>respond to abnormal events. Typically, the frame rate of<br>real-time cameras is between 24 fps and 30 fps. Therefore,<br>it is desirable to have a range of 30FPS or higher to<br>facilitate real-time gar is an improved algorium<br>respond to abnormal events. Typically, the frame rate of<br>real-time cameras is between 24 fps and 30 fps. Therefore,<br>it is desirable to have a range of 30FPS or higher to<br>facilitate real-time garbage respond to abnormal events. Typically, the frame rate of<br>real-time cameras is between 24 fps and 30 fps. Therefore,<br>it is desirable to have a range of 30FPS or higher to<br>facilitate real-time garbage detection.<br>C. Compariso real-time cameras is between 24 fps and 30 fps. Therefore,<br>real-time cameras is between 24 fps and 30 fps. Therefore,<br>it is desirable to have a range of 30FPS or higher to<br>facilitate real-time garbage detection.<br>C. Compari it is desirable to have a range of 30FPS or higher to<br>facilitate real-time garbage detection.<br>*C. Comparison Results and Analysis*<br>Yolov5's detection results and *Analysis*<br>Yolov5's detection results and *Analysis*<br>Yolov network changed to ShuffleNetV2, the standard single-stage object detection method is and the enhanced method are displayed in Fig. 6. Comparative tests were carried out in the same environment to evaluate the performance C. Comparison Results and Analysis<br>
Yolov5's detection results and Analysis<br>
Yolov5's detection results and the enhanced method are<br>
displayed in Fig. 6. Comparative tests were carried out in<br>
the same environment to evalu C. Comparison Results and Analysis<br>Yolov5's detection results and the enhanced method are<br>displayed in Fig. 6. Comparative tests were carried out in<br>the same environment to evaluate the performance of this<br>technique agains C. Comparison Results and Analysis<br>
Yolov5's detection results and the enhanced method are<br>
displayed in Fig. 6. Comparative tests were carried out in<br>
the same environment to evaluate the performance of this<br>
technique ag against the existing mainstream object<br>n models in order to confirm the efficacy of the<br>rubbish detection method suggested in this<br>experiment featured the lightweight network<br>the YOLOv5s network with its backbone<br>changed t



SSD 96.1 26 1.6 3941314<br>
Faster R-CNN 98.9 0.6 300 28295818<br>
Yolov5-shufflenet 92.6 32 7.8 860813<br>
Ours 97.9 40 10.7 4636584<br>
Table II shows that although the SSD network has a low<br>
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Yolov5-shufflenet 92.6 32 7.8 860813<br>
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processing need for devices and a straightforward<br>
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processing need for devices and a straightforward<br>
framework, its device identification speed is some Yolov5-shufflent 92.6 32 7.8 860813<br>
Ours 97.9 40 10.7 4636584<br> **Example 18 Solows** that although the SSD network has a low<br>
processing need for devices and a straightforward<br>
framework, its device identification speed is



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Ours 98.3 40 23.9 10.<br>
The aforementioned algorithms. In contrast, the current<br>
mainstream improved method, ShuffleNetV2, is replacing<br>
the YOLOv5s backbone net techniques. In this study, several enhancements are made to the accuracy requirements are material enhancement in the study of the study of the study of the study of the study, several enhancement in the study of the study of the stud Ours 98.3 40 23.9 10.7<br>
The aforementioned algorithms. In contrast, the current V. CONC<br>
mainstream improved method, ShuffleNetV2, is replacing<br>
the YOLOv5s backbone network method, which, in terms<br>
of detection speed and The aforementioned algorithms. In contrast, the current<br>
mainstream improved method, ShuffleNetV2, is replacing<br>
the YOLOv5s backbone network method, which, in terms<br>
ord detection speed and accuracy, is slower than our Th the aforementioned algorithms. In contrast, the current<br>
mainstream improved method, ShuffleNetV2, is replacing<br>
the YOLOv5s backbone network method, which, in terms<br>
ord detection speed and accuracy, is slower than our<br>
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mainstream improved method, ShuffleNetV2, is replacing<br>
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mainstream improved method, ShuffleNetV2, is replacing<br>the YOLOv5s backbone network method, which, in terms<br>orducted on the YOLOv<br>of detection speed and accuracy, is slower than our<br>sumpreconducted on the YOLOv5s are<br>this the YOLOv5s backbone network method, which, in terms<br>
ord detection speed and accuracy, is slower than our<br>
suggested approach. In conclusion, the method presented in<br>
this study offers better advantages in terms of overal of detection speed and accuracy, is slowed suggested approach. In conclusion, the method this study offers better advantages in terms performance when compared to other obje techniques. In this study, several enhancements ggested approach. In conclusion, the method presented in<br>
s study offers better advantages in terms of overall<br>
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computational and memor<br>
thingues.<br>
In this study, several enhancements a this study offers better advantages in terms of overall<br>performance when compared to other object detection<br>techniques.<br>In this study, several enhancements are made to the<br>mobile devices while<br>YOLOv5s model: the use of C3performance when compared to other object detection<br>techniques.<br>
In this study, several enhancements are made to the<br>
YOLOv5s model: the use of C3-Faster; the incorporation of<br>
the SE attention mechanism; the replacement o resources.<br>
In this study, several enhancements are made to the<br>
YOLOv5s model: the use of C3-Faster, the incorporation of<br>
the SE attention mechanism; the replacement of the securacy requirem<br>
conventional convolution wit

In this study, several enhancements are made to the<br>
YOLOv5s model: the use of C3-Faster; the incorporation of<br>
the accuracy requirement<br>
the SE attention mechanism; the replacement of the<br>
conventional convolution with Gh YOLOv5s model: the use of C3-Faster; the incorporation of<br>the accuracy requirement<br>the SE attention mechanism; the replacement of the<br>optimization of the loss function, and the<br>optimization of the loss function of the cont the SE attention mechanism; the replacement of the<br>conventional conventional convolution with Ghost convolution; and the<br>erviconventional speed and<br>equivariation of the loss function. An ablation test was<br>computated out an conventional convolution with Ghost convolution; and the<br>
optimization of the loss function. An ablation test was<br>
carried out and compared with the original model in order<br>
increased in the contribution of each component optimization of the loss function. An ablation test was<br>
carried out and compared with the original model in order<br>
to confirm the contribution of each component, as indicated<br>
improves the functional<br>
In Table III.<br>
The I carried out and compared with the original model in order<br>
improves the functionality<br>
to confirm the contribution of each component, as indicated<br>
in Table III. indicates that YOLOv5s achieves very high<br>
Nonetheless, ther to confirm the contribution of each component, as indicated<br>
in Table III. Table III indicates that YOLOv5s achieves very high<br>
detection accuracy, but it also has a lot of network<br>
parameters and requires substantial comp in Table III.<br>
Table III indicates that YOLOv5s achieves very high<br>
Monetheless, there are<br>
detection accuracy, but it also has a lot of network<br>
(1) Implementing detection accuracy, but it also has a lot of network<br>
reso algorithm.



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A lightweight and high-precision optimization study was<br>
conducted on the YOLOv5s object detection algorithm.<br>
The enhanced YOLOv5s approach considerably lowers the<br>
processing needs and parameter count of V. CONCLUSIONS<br>A lightweight and high-precision optimization study was<br>conducted on the YOLOv5s object detection algorithm.<br>The enhanced YOLOv5s approach considerably lowers the<br>processing needs and parameter count of the v. CONCLUSIONS<br>A lightweight and high-precision optimization study was<br>conducted on the YOLOv5s object detection algorithm.<br>The enhanced YOLOv5s approach considerably lowers the<br>processing needs and parameter count of the A lightweight and high-precision optimization study was<br>conducted on the YOLOv5s object detection algorithm.<br>The enhanced YOLOv5s approach considerably lowers the<br>processing needs and parameter count of the network,<br>accord systems. is eenhanced YOLOv5s approach considerably lowers the<br>ocessing needs and parameter count of the network,<br>cording to the study's findings, thus meeting the<br>mputational and memory constraints of underwater<br>bile devices while processing needs and parameter count of the network,<br>according to the study's findings, thus meeting the<br>computational and memory constraints of underwater<br>mobile devices while maintaining excellent detection<br>accuracy. Thi according to the study's findings, thus meeting the<br>computational and memory constraints of underwater<br>mobile devices while maintaining excellent detection<br>accuracy. This method demonstrates its capability to fulfill<br>the a computational and memory constraints of underwater<br>mobile devices while maintaining excellent detection<br>accuracy. This method demonstrates its capability to fulfill<br>the accuracy requirements of complex underwater<br>environme

mobile devices while maintaining excellent detection<br>accuracy. This method demonstrates its capability to fulfill<br>the accuracy requirements of complex underwater<br>environments in detection systems, finding a medium<br>ground b accuracy. This method demonstrates its capability to fulfill<br>the accuracy requirements of complex underwater<br>environments in detection systems, finding a medium<br>ground between speed and precision. As a result, it<br>successfu for the accuracy requirements of complex underwater<br>environments in detection systems, finding a medium<br>ground between speed and precision. As a result, it<br>successfully accomplishes the goals of this study and<br>improves the the absolution of the absolution and the absolution and the absolution and precision. As a result, it successfully accomplishes the goals of this study and improves the functionality of underwater trash detection systems.<br> ervolutional detween speed and precision. As a result, it<br>successfully accomplishes the goals of this study and<br>improves the functionality of underwater trash detection<br>systems.<br>Nonetheless, there are several drawbacks to recognition. (1) Implementing detection before image augmentation,<br>such as using next-generation networks to expand the<br>dataset, followed by a deep unsupervised quality<br>assessment method to evaluate and select excellent pictures<br>for u mphementary deceator economic mage diagnoniation,<br>as using next-generation networks to expand the<br>set, followed by a deep unsupervised quality<br>ssment method to evaluate and select excellent pictures<br>use as training example as using next-generation networks to expand the<br>set, followed by a deep unsupervised quality<br>ssment method to evaluate and select excellent pictures<br>use as training examples. (2) Accurately positioning<br>its for underwater r stet, followed by a deep unsupervised quality<br>
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use as training examples. (2) Accurately positioning<br>
its for underwater robots involves combining<br>
idimensional loca ssment method to evaluate and select excellent pictures<br>use as training examples. (2) Accurately positioning<br>the formular method is involved complining<br>idimensional localization data with multifaceted object<br>gnition.<br>REFER for use as training examples. (2) Accurately positioning<br>targets for underwater robots involves combining<br>multidimensional localization data with multifaceted object<br>recognition.<br><br>EEFERENCES<br>[1] Y. W. Cheng, J. N. Zhu, M.

## **REFERENCES**

- environment: A review of their sources, distribution Real-Time New Remaining P.V. W. Cheng, J. N. Zhu, M. X. Jiang, J. Fu, C. S. Pang, P. D. Wang, K. Sankaran, O. Onabola, Y. M. Liu, D. B. Liu and Y. Bengio, "FloW: A Datas 2013 ION Underwater Tobots Involves Combining<br>
idimensional localization data with multifaceted object<br>
ginition.<br>
REFERENCES<br>
Y. W. Cheng, J. N. Zhu, M. X. Jiang, J. Fu, C. S. Pang, P. D. Wang,<br>
K. Sankaran, O. Onabola, Y idimensional localization data with multifaceted object<br>gnition.<br>
REFERENCES<br>
Y. W. Cheng, J. N. Zhu, M. X. Jiang, J. Fu, C. S. Pang, P. D. Wang,<br>
K. Sankaran, O. Onabola, Y. M. Liu, D. B. Liu and Y. Bengio,<br>
"FloW: A Data REFERENCES<br>
(1) Y. W. Cheng, J. N. Zhu, M. X. Jiang, J. Fu, C. S. Pang, P. D. Wang,<br>
K. Sankaran, O. Onabola, Y. M. Liu, D. B. Liu and Y. Bengio,<br>
"FloW: A Dataset and Benchmark for Floating Waste Detection in<br>
Inland Wate REFERENCES<br>
Y. W. Cheng, J. N. Zhu, M. X. Jiang, J. Fu, C. S. Pang, P. D. Wang,<br>
K. Sankaran, O. Onabola, Y. M. Liu, D. B. Liu and Y. Bengio,<br>
"FloW: A Dataset and Benchmark for Floating Waste Detection in<br>
Inland Waters," REFERENCES<br>
X. W. Cheng, J. N. Zhu, M. X. Jiang, J. Fu, C. S. Pang, P. D. Wang,<br>
K. Sankaran, O. Onabola, Y. M. Liu, D. B. Liu and Y. Bengio,<br>
"FloW: A Dataset and Benchmark for Floating Waste Detection in<br>
Inland Waters," KEFERENCES<br>
KEFERENCES<br>
K. W. Cheng, J. N. Zhu, M. X. Jiang, J. Fu, C. S. Pang, P. L<br>
K. Sankaran, O. Onabola, Y. M. Liu, D. B. Liu and Y.<br>
Irland Watters," Proceedings of the IEEE/CVF Inter<br>
Irland Watters," Proceedings o [1] Y. W. Cheng, J. N. Zhu, M. X. Jiang, J. Fu, C. S. Pang, P. D. Wang,<br>K. Sankaran, O. Onabola, Y. M. Liu, D. B. Liu and Y. Bengio,<br>"FloW: A Dataset and Benchmark for Floating Waste Detection in<br>Inland Waters," Proceeding
- K. Sankaran, O. Onabola, Y. M. Luu, D. B. Luu and Y. Bengio, "FloW: A Dataset and Benchmark for Floating Waste Detection in Inland Waters," Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), pp "FloW: A Dataset and Benchmark for Floating Waste Detection in<br>
Inland Waters," Proceedings of the IEEE/CVF International<br>
Conference on Computer Vision (ICCV), pp. 10953-10962, 2021.<br>
R. Coyle, G. Hardiman, Driscoll, "Mic Inland Waters," Proceedings of the IEEE/CVF International<br>
Conference on Computer Vision (ICCV), pp. 10953-10962, 2021.<br>
[2] R. Coyle, G. Hardiman, Driscoll, "Microplastics in the marine<br>
environment: A review of their sou Conterence on Computer Vision (ICCV), pp. 10953-10962, 2021.<br>
R. Coyle, G. Hardiman, Driscoll, "Microplastics in the marine<br>
environment: A review of their sources, disribution processes,<br>
uptake and exchange in ecosystems
- R. Coyle, G. Hardıman, Driscoll, "Microplastic<br>environment: A review of their sources, distri-<br>uptake and exchange in ecosystems," Case Studies<br>Environmental Engineering, vol. 2, pp. 100010, 202<br>Cr. P. Zhang and H. W. Peng environment: A review of their sources, distribution processes,<br>uptake and exchange in cosystems," Case Studies in Chemical and<br>Environmental Engineering, vol. 2, pp. 100010, 2020.<br>[3] Z. P. Zhang and H. W. Peng, "Deeper a uptake and exchange in ecosystems," Case Studies in Chemical and<br>Environmental Engineering, vol. 2, pp. 100010, 2020.<br>
Z. P. Zhang and H. W. Peng, "Deeper and Wider Siamese Networks<br>
for Real-Time Visual Tracking," 2019 IE Environmental Engineering, vol. 2, pp. 100010, 2020.<br>
Z. P. Zhang and H. W. Peng, "Deeper and Wider Siamese Networks<br>
for Real-Time Visual Tracking," 2019 IEEE/CVF Conference on<br>
Computer Vision and Pattern Recognition (CV
- 
- 
- 
- [3] Z. P. Zhang and H. W. Peng, "Deeper and Wider Siamese Networks<br>for Real-Time Visual Tracking," 2019 IEEE/CVF Conference on<br>Computer Vision and Pattern Recognition (CVPR), Long Beach, CA,<br>USA, pp. 4591-4600, 2019.<br>[4] F for Real-Time Visual Tracking," 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA, pp. 4591-4600, 2019.<br>
F. Y. Wang, J. J. Zhang, et al, "Where does AlphaGo go: from church-tur Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA, pp. 4591-4600, 2019.<br>F. Y. Wang, J. J. Zhang, et al, "Where does AlphaGo go: from church-turing thesis to AlphaGo thesis and beyond," IEEE/CAA Journal of USA, pp. 4591-4600, 2019.<br>
F. Y. Wang, J. J. Zhang, et al, "Where does AlphaG<br>
church-turing thesis to AlphaGo thesis and beyond,"<br>
Journal of Automatica Sinica, pp. 113-120, 2016.<br>
D. Yuan and Y. Xu, "Lightweight Vehicle
- **Engineering Letters**<br>
[8] W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>
Proposal-Fusion Among Multiple Images for Underwater Object<br>
Detection, International Conference on Acoustics, Speech, and<br>
Signal Proces **Engineering Letters**<br>
W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>
Proposal-Fusion Among Multiple Images for Underwater Object<br>
Detection, International Conference on Acoustics, Speech, and<br>
Signal Processing **Engineering Letters**<br>W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>Proposal-Fusion Among Multiple Images for Underwater Object<br>Detection, International Conference on Acoustics, Speech, and<br>Signal Processing(ICA **Engineering Letter**<br>
W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>
Proposal-Fusion Among Multiple Images for Underwater Object<br>
Detection, International Conference on Acoustics, Speech, and<br>
Signal Processing( **Engineering Letters**<br>
[8] W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>
Proposal-Fusion Among Multiple Images for Underwater Object<br>
Detection, International Conference on Acoustics, Speech, and<br>
Signal Proces **Engineering Letters**<br>
W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>
Proposal-Fusion Among Multiple Images for Underwater Object<br>
Detection, International Conference on Acoustics, Speech, and<br>
Signal Processing W. H. Lin, J. X. Zhong, S. Liu, T. Li an<br>Proposal-Fusion Among Multiple Images for<br>Detection, International Conference on Acot<br>Signal Processing(ICASS P). pp. 2588-2592, 202<br>P. F. Shi, X. W. Xu, J. J. Ni, et al, "Underwate **Engineering Letters**<br>
[8] W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>
Proposal-Fusion Among Multiple Images for Underwater Object<br>
Detection, International Conference on Acoustics, Speech, and<br>
Signal Proces **Engineering Letters**<br>
W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>
Proposal-Fusion Among Multiple Images for Underwater Object<br>
Detection, International Conference on Acoustics, Speech, and<br>
Signal Processing **Example 12, 19.13**<br>
W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>
Proposal-Fusion Among Multiple Images for Underwater Object<br>
Detection, International Conference on Acoustics, Speech, and<br>
Signal Processing(I [8] W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>
Proposal-Fusion Among Multiple Images for Underwater Object<br>
Detection, International Conference on Acoustics, Speech, and<br>
Signal Processing(ICASS P). pp. 2588 W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>Proposal-Fusion Among Multiple Images for Underwater Object<br>Detection, International Conference on Acoustics, Speech, and<br>Signal Processing(ICASS P). pp. 2588-2592, W. H. Lin, J. X. Zhong, S. Liu, T. Li and G. Li. Roimix:<br>Proposal-Fusion Among Multiple Images for Underwater Object<br>Detection, International Conference on Acoustics, Speech, and<br>Signal Processing(ICASS P). pp. 2588-2592,
- 
- 
- 
- [12] B. Zheng, S. Lui, 1. Li and G. Li. Kommx:<br>
Proposal-Fusion Among Multiple Images for Underwater Object<br>
Detection, International Conference on Acoustics, Speech, and<br>
Signal Processing(ICASS P). pp. 2588-2592, 2020.<br> Proposal-Puson Among Wultipe Images for Underwater Object<br>
Detection, International Conference on Acoustics, Speech, and<br>
Signal Processing(ICASS P). pp. 2588-2592, 2020.<br>
P. F. Shi, X. W. Xu, J. J. Ni, et al, "Underwater Detection, international Conference on Acoustics, speech, and<br>Signal Processing(ICASS P). pp. 2588-2592, 2020.<br>P. F. Shi, X. W. Xu, J. J. Ni, et al, "Underwater Biological Detection<br>Algorithm Based on Improved Faster-RCNN, Signal Processing(CASS P). pp. 2566-2592, 2020.<br>
P. F. Shi, X. W. Xu, J. J. Ni, et al, "Underwater Biological Detect<br>
Algorithm Based on Improved Faster-RCNN," Water, vol. 13, no.<br>
Algorithm Based on Improved Faster-RCNN,"
- [13] J. R. W. A. J. J. W. et al., Underwater Blougkail Detection<br>
[10] L. Wei, S. Kong, Y. Wu, et al. "Image Semantic Segmentation of<br>
Underwater Garbage with Modified U-Net Architecture Model,"<br>
Sensors, vol. 22, no. 17, Argonium Dasea on improved Paster-KCNN, Water, Vol. 13, 10. 17,<br>
I. Wei, S. Kong, Y. Wu, et al. "Image Semantic Segmentation of<br>
Underwater Garbage with Modified U-Net Architecture Model,"<br>
Sensors, vol. 22, no. 17, pp. 65 pp. 2+20, 2021.<br>
2- Wei, S. Kong, Y. Wu, et al. "Image Semantic Segmentation of<br>
Underwater Garbage with Modified U-Net Architecture Model,"<br>
Sensors, vol. 22, no. 17, pp. 6546 – 6557, 2022.<br>
Detection Algorithm Based on I L. wei, S. Kong, T. W., et al. Image Sentantu esguieration of<br>Underwater Garbage with Modified U-Net Architecture Model,"<br>Sensors, vol. 22, no. 17, pp. 6546 - 6557, 2022.<br>B. Zhang, X. X. Zhang and Z. Li, "An Efficient Face Conterwater Garoage with Modined O-Net Atchite<br>
Sensors, vol. 22, no. 17, pp. 6546 - 6557, 2022.<br>
B. Zhang, X. X. Zhang and Z. Li, "An Efficient Face<br>
Detection Algorithm Based on Improved YOLOv3<br>
Letters, vol. 30, no. 4, Sensors, vol. 22, no. 1/, pp. 03-940 – 035/, 2022.<br>
[11] B. Zhang, X. X. Zhang and Z. Li, "An Efficient Face Mask Wearing<br>
Detection Algorithm Based on Improved YOLOv3," Engineering<br>
Letters, vol. 30, no. 4, pp. 1493-1503, B. Znang, A. X. Znang and Z. Li, "An Entricent race Mass wearing<br>Detection Algorithm Based on Improved YOLOv3," Engineering<br>Letters, vol. 30, no. 4, pp. 1493-1503, 2022.<br>Z. H. Zheng, P. Wang, D. W. Ren, et al. "Enhancing G Detection Algorithm Based on improved YOLOV3," Engineering<br>
Letters, vol. 30, no. 4, pp. 1493-1503, 2022.<br>
Z. H. Zheng, P. Wang, D. W. Ren, et al. "Enhancing Geometric<br>
Factors in Model Learning and Inference for Object De Letters, vol. 30, no. 4, pp. 1493-1503, 2022.<br>
Z. H. Zheng, P. Wang, D. W. Ren, et al. "Enh<br>
Factors in Model Learning and Inference for Obj<br>
Instance Segmentation," In IEEE Transactions on<br>
52, no. 8, pp. 8574 – 8586, 202 [12] Z. H. Zeneng, P. wang, D. W. Ken, et al. "Ennameng Geometric Tection and<br>
Instance Segmentation," In IEEE Transactions on Cybernetics, vol.<br>
52, no. 8, pp. 8574 - 8586, 2022.<br>
[13] J. R. Chen, S. H. Kao, H. He, W. P. ractors in Model Learning and Interence for Object Detection and<br>Instance Segmentation," In IEEE Transactions on Cybernetics, vol.<br>52, no. 8, pp. 8574 - 8586, 2022.<br>J. R. Chen, S. H. Kao, H. He, W. P. Zhuo, S. Wen, C. H. L mstance Segmentation," in IEEE Transactions on Cybernetics, vol.<br>52, no. 8, pp. 8574 – 8586, 2022.<br>J. R. Chen, S. H. Kao, H. He, W. P. Zhuo, S. Wen, C. H. Lee and S.<br>H. Chan. "Don't Walk: Chasing Higher FLOPS for Faster Ne 52, no. 8, pp. 85/4 – 8586, 2022.<br>
[13] J. R. Chen, S. H. Kao, H. He, W. P. Zhuo, S. Wen, C. H. Lee and S.<br>
H. Chan, "Don't Walk: Chasing Higher FLOPS for Faster Neural<br>
Networks," In Proceedings of the IEEE/CVF Conference
- 
- 
- J. R. Chen, S. H. Kao, H. He, W. P. Zhuo, S. Wen, C. H. Lee and S.<br>H. Chan. "Don't Walk: Chasing Higher FLOPS for Faster Neural<br>Networks," In Proceedings of the IEEE/CVF Conference on<br>Computer Vision and Pattern Recognitio H. Chan. "Don't Walk: Chasing Higher HLOPS for Faster Neural<br>Networks," In Proceedings of the IEEE/CVF Conference on<br>Computer Vision and Pattern Recognition (CVPR), pp.<br>12021–12031, 2023.<br>K. Han, Y. Wang, Q. Tian, J. Guo a Networks," In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 12021–12031, 2023.<br>
I2021–12031, 2023.<br>
K. Han, Y. Wang, Q. Tian, J. Guo and C. Xu, "GhostNet: More Features From Computer Vision and Pattern Recognition (CVPR), pp. 12021–12031, 2023.<br>
12021–12031, 2023.<br>
K. Han, Y. Wang, Q. Tian, J. Guo and C. Xu, "GhostNet: More<br>
Features From Cheap Operations," 2020 IEEE/CVF Conference on<br>
Compute