Real-time ML Algorithms for The Detection of Dangerous Objects in Critical Infrastructures

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Abstract

Critical infrastructure is high-level priority area in the conditions of a hybrid large-scale war in Ukraine. Real-time threats monitoring should be provided in both cyber and physical space. This study analyzes existing machine learning (ML) algorithms in real time, compared their advantages and disadvantages, determined the main criteria and chose the optimal algorithm for protecting people and critical infrastructure in the conditions of a hybrid large-scale war. The optimal algorithm was defined by criteria; it can be quickly learned detect the desired objects in a limited time, has good object finding accuracy, and does not require large server capacities. The novelty of the work lies in multicriteria analysis of real-time object detection algorithms by proposed criteria as well as defining optimal algorithm that can be used to detect dangerous objects in critical infrastructures. Given results will be useful for developing ML-based real-time monitoring system for critical infrastructure.

Keywords 1

cyber warfare, critical infrastructure, machine learning algorithms, neural networks, real-time

1. Introduction

In the conditions of a hybrid large-scale war in Ukraine, the number of cyber threats is increasing, and technologies that were reliable yesterday, require rapid improvement, modernization and quality testing today, because the lives of our people and the integrity of critical infrastructure depend on it. Machine learning (ML) technologies are emerging and improving to avoid human error.

ML algorithms are becoming increasingly popular for real-time detection of dangerous objects: such as fires, smoke, aviation and missile threats on critical infrastructure such as bridges, dams and nuclear, hydroelectric and other power plants.

In wartime, conventional methods of fire detection, such as smoke detectors and thermal imaging cameras, can be slow and not always accurate. Real-time ML algorithms can quickly and accurately detect fires in real time by analyzing video from cameras located throughout the facility. This allows for faster response times and can potentially prevent damage to critical infrastructure and injury to personnel.

Also, ML algorithms can quickly and accurately detect and track in real time using video from cameras placed around the object aircraft and UAVs that can potentially be used for malicious purposes, such as espionage, or terrorist attacks on critical objects. infrastructure. This can help with air traffic management and improve security at critical infrastructure facilities.

IntelITSIS'2023: 4th International Workshop on Intelligent Information Technologies and Systems of Information Security, March 22–24, 2023, Khmelnytskyi, Ukraine
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CEUR Workshop Proceedings (CEUR-WS.org)

It has been proven that these algorithms are highly effective in detecting potential threats and providing early warning and neutralization to prevent potential disasters in the conditions of a large-scale war in Ukraine [1].

The ***main objective*** of this study is multicriteria analysis and defining the optimal real-time ML algorithm, that can effectively find threats for quick neutralization and increased security at critical infrastructure facilities.

2. Real-time ML algorithms: advantages and disadvantages

Analysis showed 10 most effective real-time object detection algorithms, such as: RetinaNet, Faster R-CNN, Mask R-CNN, R-CNN, R-FCN, YOLACT, CornerNet, CenterNet, EfficientDet,You Only Look Once (YOLO) and Single Shot MultiBox Detector (SSD). Let's analyze these in detail.

2.1. YOLO

YOLO (You Only Look Once) is a real-time object detection algorithm that uses a single convolutional neural network (CNN) to predict bounding boxes and class probabilities for objects in an image. It divides the image into a grid of cells, and each cell assumes a set of bounding boxes and class probabilities.

YOLO is known for its speed and real-time performance, but it may not be as accurate as other algorithms. A model of the algorithm can be seen in Fig. 1.

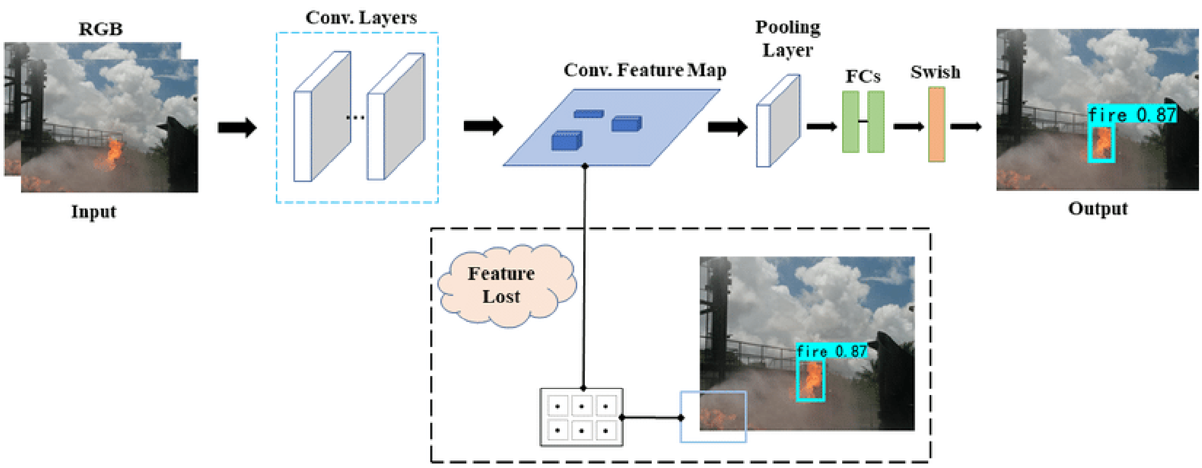

Figure 1: YOLO algorithm model [2]

Advantages of YOLO (You Look Only Once):

- High speed and real-time performance, making it well suited for video and web cameras.
- Can detect several objects in the image at the same time.
- Simple architecture and ease of implementation.
- Can handle multiple frames per second

Disadvantages of YOLO:

- Insufficient accuracy compared to other algorithms, especially for small objects and fine-grained classes.
- Sensitivity to the location and size of objects in the image [3].

2.2. SSD

Single Shot MultiBox Detector (SSD) is a real-time object detection algorithm that uses a single CNN to predict bounding boxes and class probabilities in an image.

It uses a technique called binding blocks to provide multiple bounding boxes for objects of different sizes and proportions.

SSD is known for its high performance and is well suited for real-time applications. A model of the algorithm can be seen in Fig. 2.

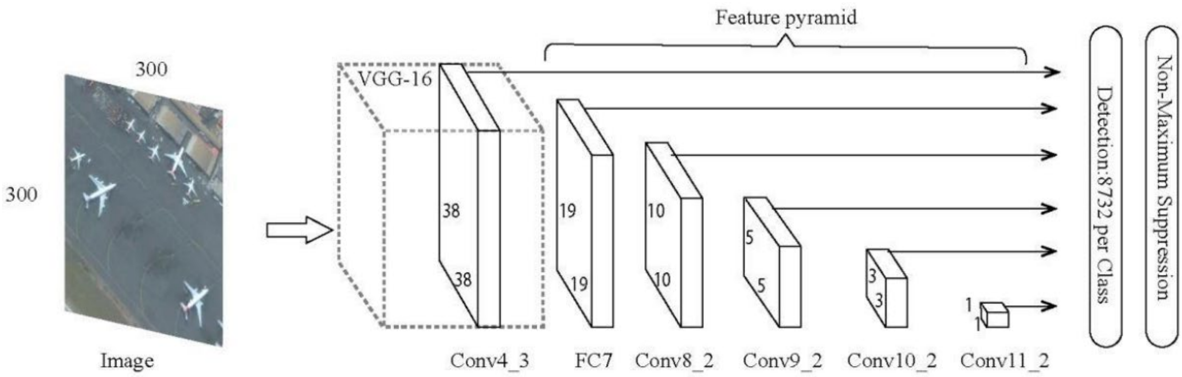

Figure 2: Single Shot MultiBox Detector algorithm model [4]

Advantages of Single Shot MultiBox Detector:

- High performance and real-time capabilities make it ideal for real-time applications.
- Can work with objects of different scales and proportions.
- Simple architecture and ease of implementation.
- Can handle multiple frames per second

Disadvantages of SSD:

- Insufficient accuracy of detection of small objects or small classes [5].

2.3. RetinaNet

RetinaNet is a real-time object detection algorithm that addresses the imbalance between foreground and background classes in object detection.

It uses a technique called focal loss to reduce the effect of light negative samples and improve the detection of rare objects. A model of the algorithm can be seen in Fig. 3.

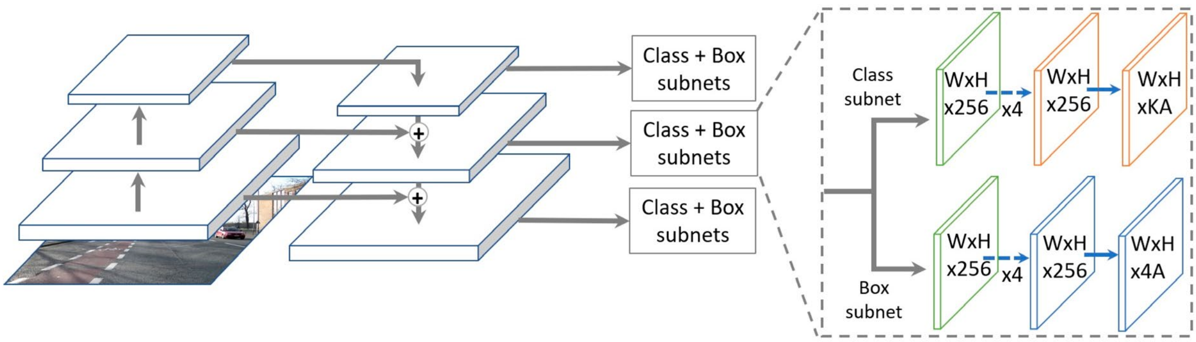

Figure 3: RetinaNet algorithm model [6]

Advantages of RetinaNet:

- Good accuracy, robust to scale variations and works well on small objects
- Fixes an imbalance between foreground and background classes when detecting objects.

Disadvantages of RetinaNet:

- High computational cost compared to other real-time algorithms [7].

2.4. Faster R-CNN

Faster R-CNN is a real-time object detection algorithm that uses a Regional Proposition Network (RPN) to generate object proposals and a separate CNN to classify and locate objects in the proposals. It is known for its accuracy, but may not be as fast as other algorithms.

A model of the algorithm can be seen in Fig. 4 [8].

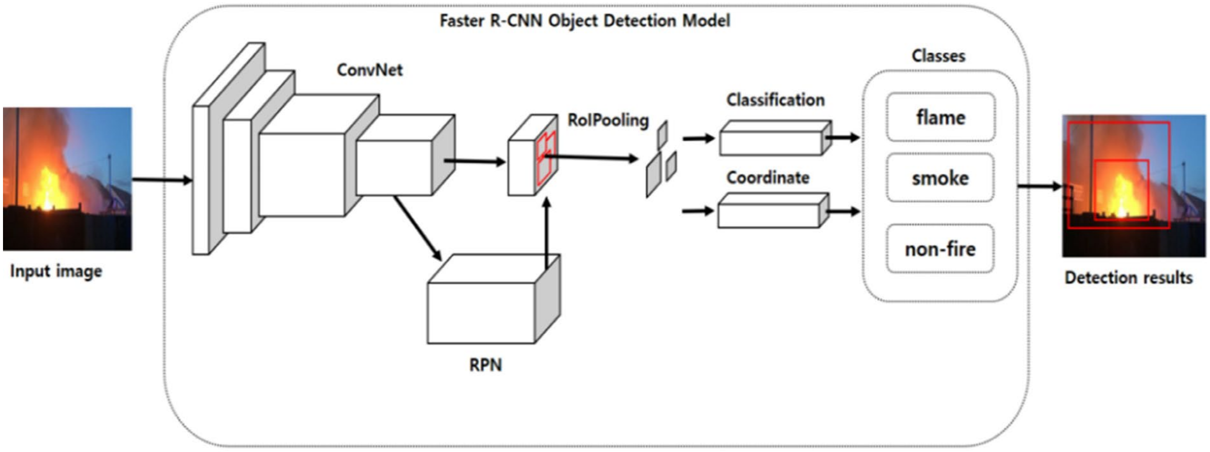

Figure 4: Faster R-CNN algorithm model [9]

Advantages of Faster R-CNN:

- High accuracy and the ability to process objects of different scales and proportions.

Disadvantages of Faster R-CNN:

- High computational cost, making it less suitable for real-time applications [10].

2.5. R-FCN

R-FCN is a real-time feature detection algorithm that uses fully convolutional convolution (FCN) to predict feature bounding boxes and class probabilities.

It uses position-sensitive score maps to improve object detection accuracy. A model of the algorithm can be seen in Fig. 5.

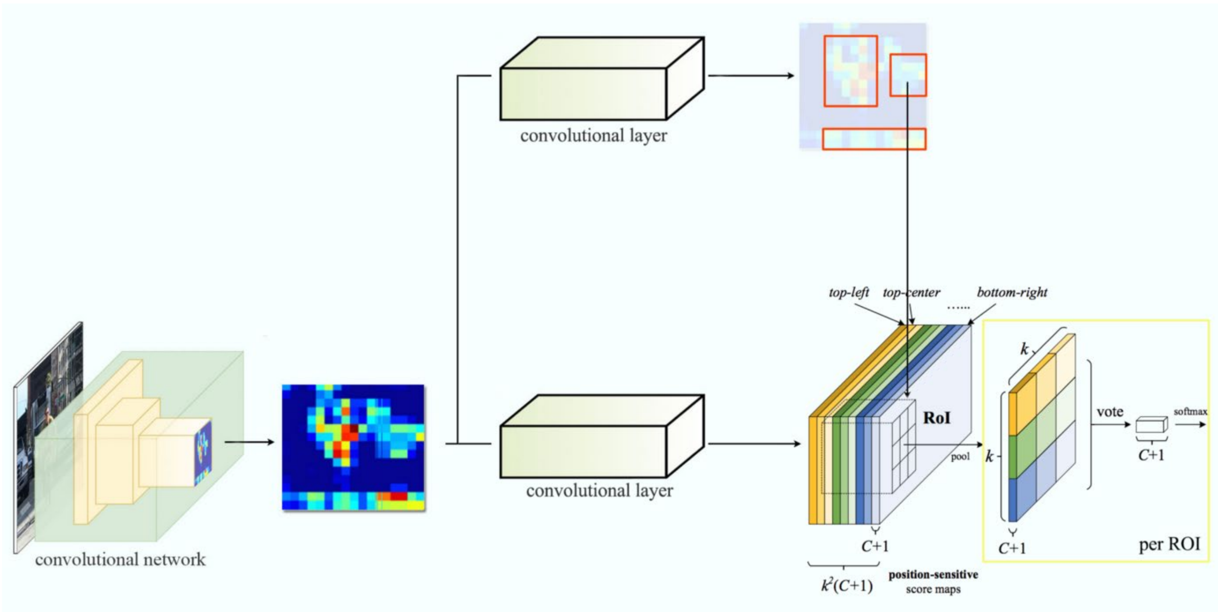

Figure 5: Model of the R-FCN algorithm [11]

Advantages of R-FCN:

- Improved object detection accuracy thanks to the use of position-sensitive score maps.

Disadvantages of R-FCN:

- Not as fast as other algorithms and may not handle small objects or fine-grained classes as well as other algorithms [11].

2.6. Mask R-CNN

Mask R-CNN is an extension of Faster R-CNN that adds an additional branch to the network to predict feature masks in addition to bounding boxes and class probabilities. A model of the algorithm can be seen in Fig. 6.

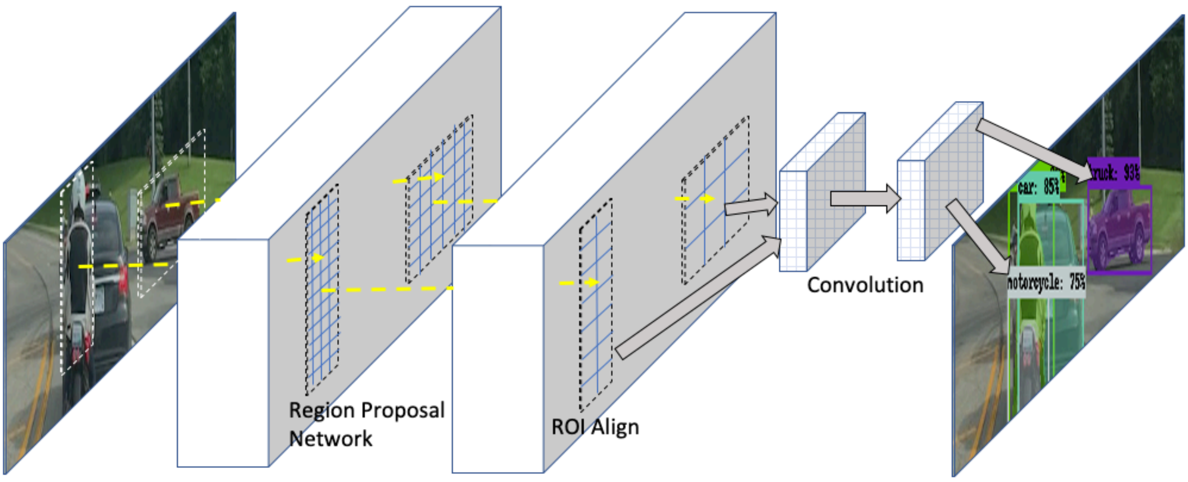

Figure 6: Mask R-CNN algorithm model [12]

Advantages of Mask R-CNN:

- Improved object detection accuracy due to the use of instance segmentation masks.
- Ability to perform segmentation at the instance level.

Disadvantages of Mask R-CNN:

- High computational cost, making it less suitable for real-time applications [12].

2.7. YOLACT

YOLACT is a real-time object detection algorithm that uses a single CNN to predict both bounding boxes and class probabilities as well as instance segmentation masks.
A model of the algorithm can be seen in Fig. 7.

Advantages of YOLACT:

- Real-time performance, efficiency, and the ability to perform instance-level segmentation.

Disadvantages of YOLACT:

- Insufficient accuracy for small objects and fine-grained classes [13].

2.8. CornerNet

CornerNet is a real-time object detection algorithm that uses key points instead of bounding boxes for object detection. It uses two separate networks: one to determine the upper left and lower right corners, and another to predict the class of the object.

A model of the algorithm can be seen in Fig. 7.

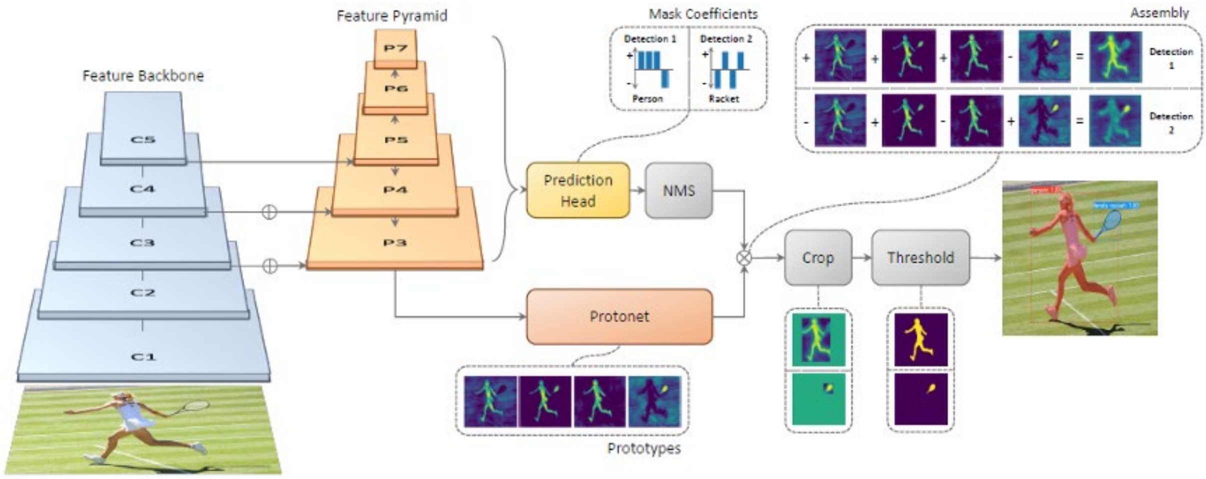

Figure 7: Model YOLACT algorithm [13]

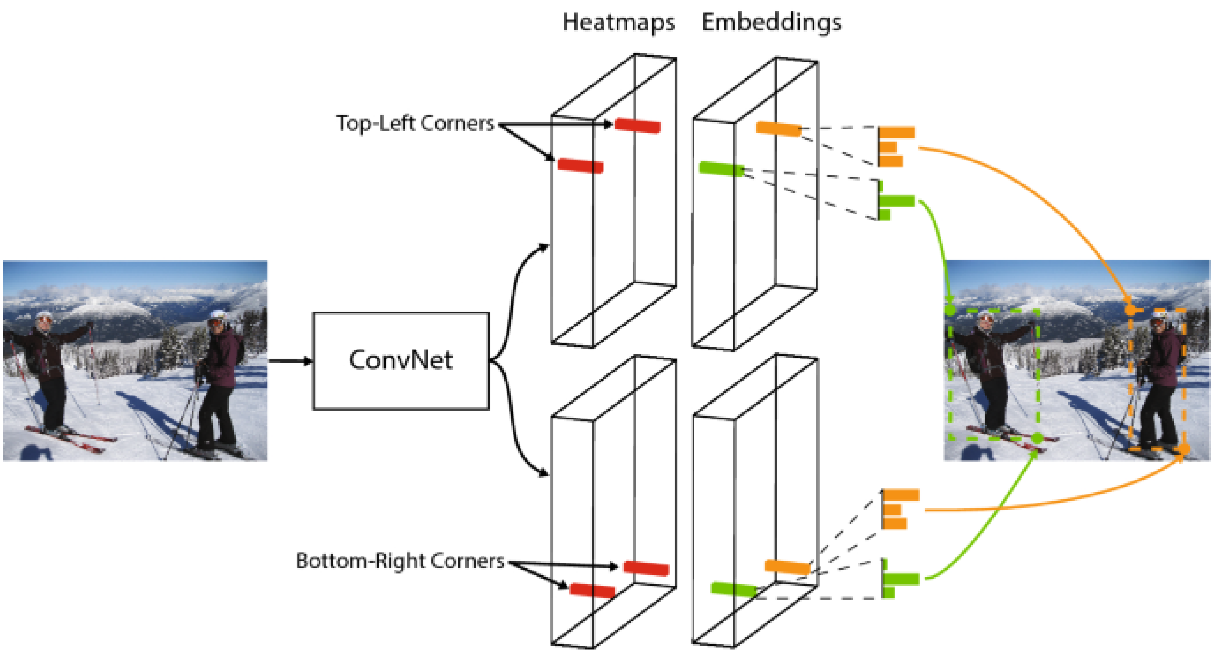

Figure 8: Model CornerNet algorithm [14]

Advantages of CornerNet:

- Good results in detecting small objects due to the use of key points instead of bounding boxes.

Disadvantages of CornerNet:

- High computational cost, making it less suitable for real-time applications [14].

2.9. CenterNet

CenterNet is a real-time object detection algorithm that uses keypoints instead of bounding boxes for object detection. It uses a single CNN to predict the object center and size, as well as the class probability.

A model of the CenterNet algorithm can be seen in Fig. 9.

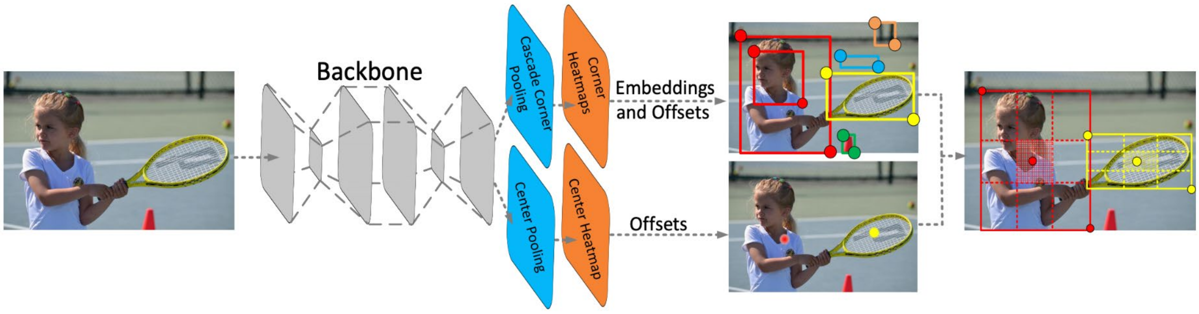

Figure 9: CenterNet algorithm model [15]

Advantages of CenterNet:

- Good results in detecting small objects due to the use of key points instead of bounding boxes.

Disadvantages of CenterNet:

- High computational cost, making it less suitable for real-time applications [15].

2.10. EfficientDet

EfficientDet is a real-time object detection algorithm that uses a single CNN to predict both bounding boxes and class probabilities, but uses a technique called complex scaling to improve the accuracy and efficiency of the detection network.

A model of the EfficientDet algorithm can be seen in Fig. 10.

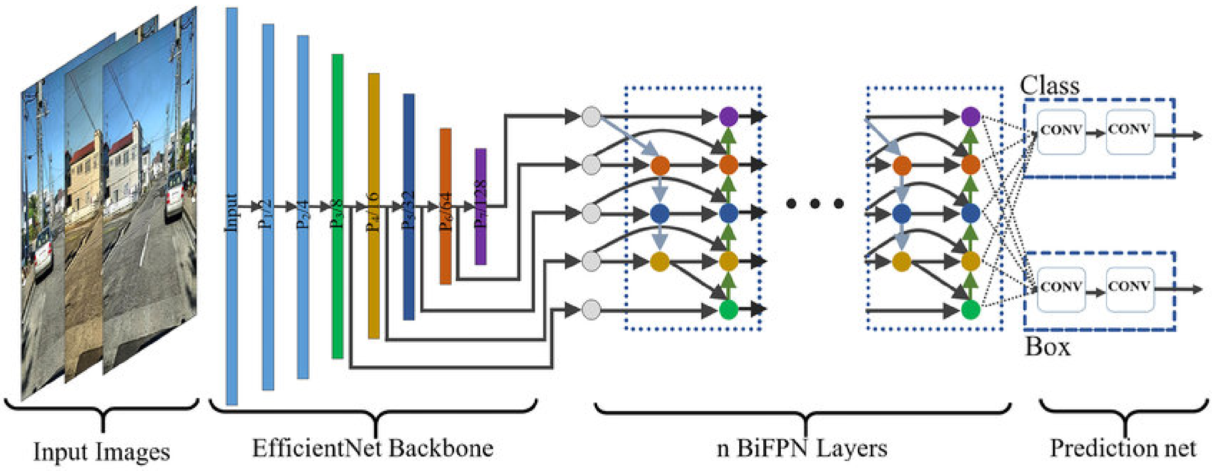

Figure 10: EfficientDet algorithm model [16]

Advantages of EfficientDet:

- Increased accuracy and efficiency through the use of sophisticated scaling.

Disadvantages of EfficientDet:

- May not be as fast as other real-time algorithms [16].

3. Results and discussion

It is worth noting that the best algorithm for a particular application will depend on the specific requirements of the task and the available hardware.

In general, there is a trade-off between speed, accuracy, and computing resources when choosing a real-time object detection algorithm.

When choosing an algorithm for real-time object detection on critical infrastructure facilities, it is important to consider the specific requirements of the application, such as the type of objects to be detected, the size of the objects, the complexity of the scenes, and the required processing speed. In addition, it is also important to consider available computing resources and data availability.

For example, if you need to detect small objects or detailed classes in a real-time application, algorithms such as RetinaNet, Faster R-CNN, R-FCN, Mask R-CNN, EfficientDet – may be more suitable because they have higher accuracy for these types of objects, but may require more computing resources and are not as fast as other counterparts.

Such algorithms as: YOLACT, CornerNet, CenterNet can process information faster, require less computing resources, but have the lowest accuracy detection of small objects.

However, if you need to perform object detection not only from images, but also from videos and webcams in real time on a low-power device, or with limited computing resources, algorithms such as YOLO and SSD may be more optimal and appropriate.

To protect critical infrastructure [17-23], the optimal solution would be to use an algorithm YOLO, the learning rate of this neural network is high and it does not require a lot of computing resources and has good accuracy. Speed, accuracy and the price of computing equipment determine optimal use [24-27].

Because these criteria determine the speed of decision-making by the situational center to neutralize potential threats and save people's lives.

Table 1: Comparison of real-time object detection algorithms

Algorithm	Accuracy of detection of large objects	Accuracy of detection of small objects	Calculated cost	Processing speed
YOLO	High	Average	Low	High
SSD	High	Average	Low	High
RetinaNet	High	High	High	Average
Faster R-CNN	High	High	High	Average
R-FCN	High	High	High	Low
Mask R-CNN	High	High	High	Low
YOLACT	Average	Low	Average	High
CornerNet	Average	Average	High	Average
CenterNet	High	Average	Average	Average
EfficientDet	High	High	High	Low

4. Conclusions and future research studies

This study analyzes existing real-time object detection algorithms, such as: RetinaNet, Faster R-CNN, Mask R-CNN, R-CNN, R-FCN, YOLACT, CornerNet, CenterNet, EfficientDet,You Only Look Once (YOLO) and Single Shot MultiBox Detector (SSD).

Their advantages and disadvantages were compared and the main criteria were determined (accuracy detection of large and small objects, at computational cost and processing speed) as well as optimal algorithm for protection critical infrastructure [28-32] in the conditions of a full-scale war in Ukraine was defined.

The optimal algorithm is YOLO, which can be quickly learned detect the desired objects in a limited time, has good object finding accuracy (which depends on the quality and number of training epochs), and does not require large server capacities (cloud server computing can also be used), other real-time ML algorithms require larger server capacities, have low learning speed, although they can be more accurate in detection of small objects.

The novelty of the work lies in multicriteria analysis of real-time object detection algorithms by proposed criteria as well as defining optimal algorithm that can be used to detect dangerous objects in critical infrastructures.

In any case, using these algorithms together and combining them using ensemble techniques (for example: using multiple algorithms to train a common model faster and more accurately) can improve the overall performance of the system.

In addition, it is also important to note that ML algorithms are not perfect, and the results should be checked by specialists of the situation center and information processing, who will be able to evaluate the quality of the trained model for finding objects, and improve the quality of the algorithm model by increasing the number of training epochs, this is important especially in critical infrastructure where a small mistake can cause a major disaster.

In the future, given results will be useful for developing ML-based real-time monitoring system for critical infrastructure.

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