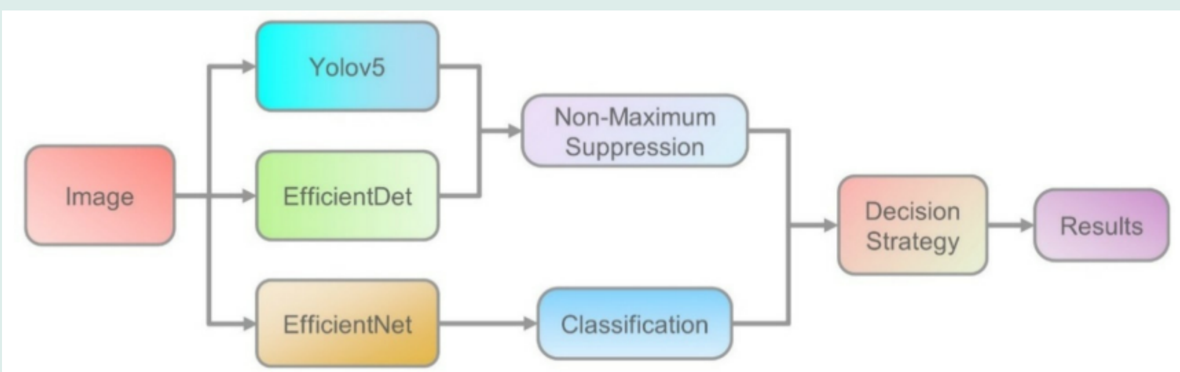
20210310

▼ A Forest Fire Detection System Based on Ensemble Learning

https://www.mdpi.com/1999-4907/12/2/217/htm

Method



1. two individual learners Yolov5 (**better at learning long-area fires**) & EfficientDet (**make a complementary detection**) are integrated to accomplish fire detection process. These tend to focus too much on local information (ground truth), but ignore global information, which may lead to false positive.

2. The 3rd learner EfficientNet is responsible for **learning global information to avoid false positive**, which acts as a **binary classifier**, responsible for learning the whole image to determine whether the image contains fire objects.
3. Finally, the object detection results, and image classification results are sent into a **decision strategy module**, in which if the image is considered to contain fire objects, retaining object detection results, otherwise ignoring them.

Keywords

forest fire detection, deep learning, ensemble learning, Yolov5, EfficientDet, EfficientNet.

Background

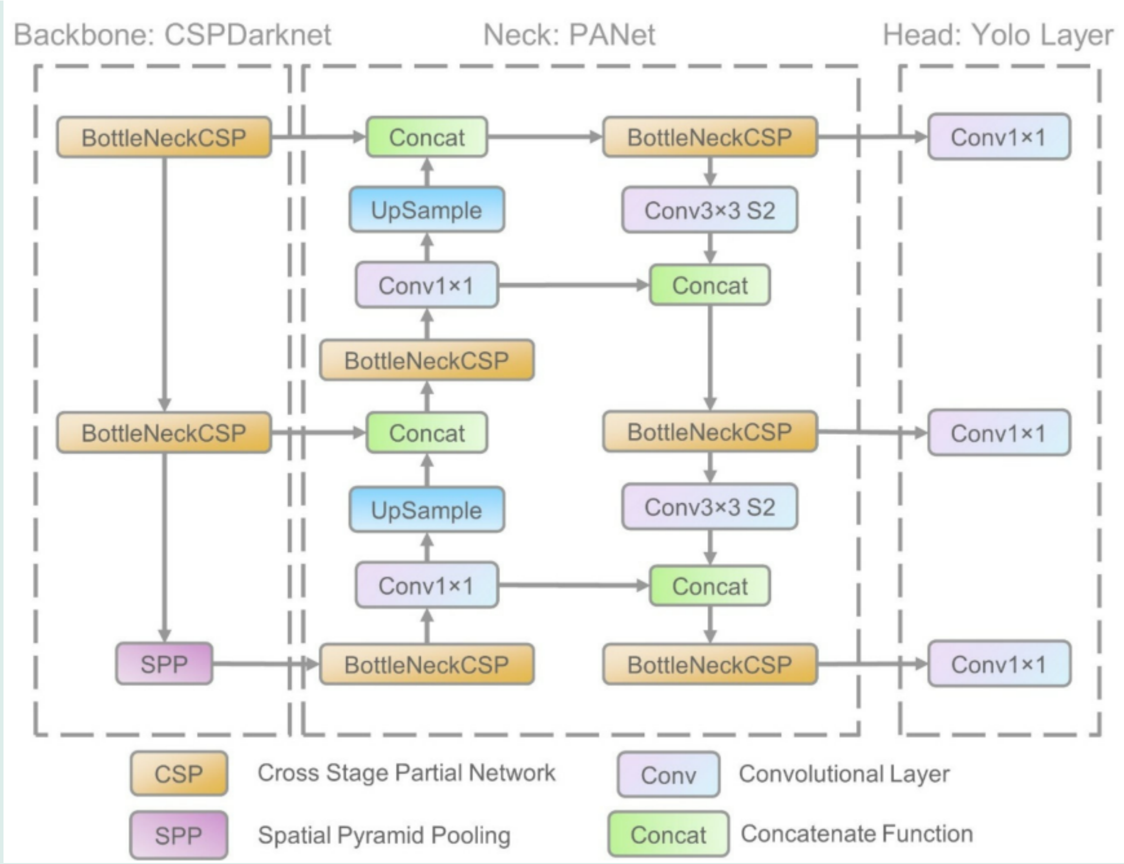
Most researchers tend to only assign individual learners to perform object detection tasks, whish is considered unreliable, since it may lead to false positive.

Dataset

BowFire, FD-datase, ForestryImages, VisiFire, etc. Creating **10,581 images**, with 2976 forest fire images and 7605 non-fire images.

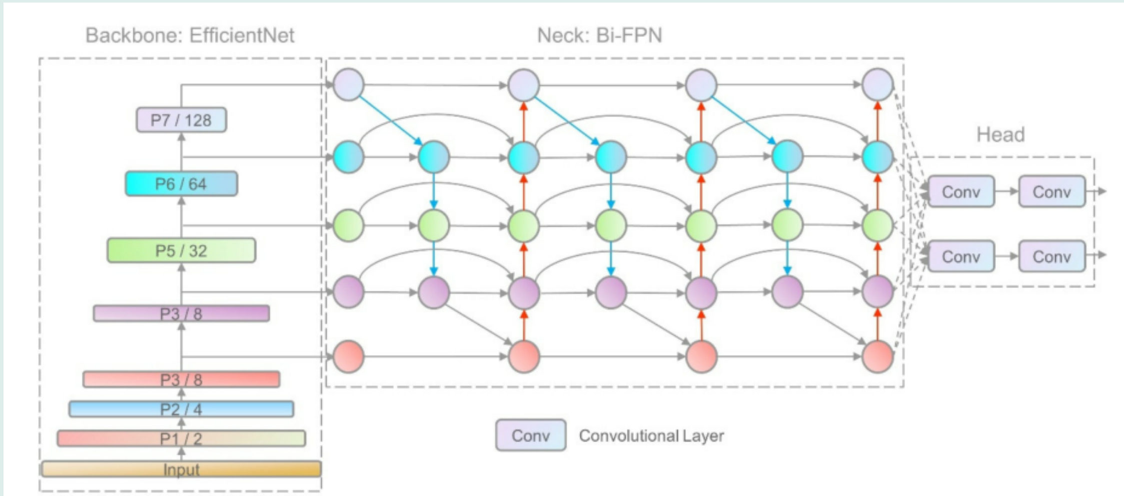
Algorithms introduction

▼ Yolov5



- **Backbone: CSPDarknet.** CSPNet solves the problem of repeated gradient information in large-scale backbones, and integrates the gradient changes into the feature map, thereby decreasing the parameters and FLOPS (floating-point operations per second) of model, which not only ensures the inference speed and accuracy , but also reduces the model size.
- **Neck: PANet (path aggregation network).** PANet adopts a new feature pyramid network (FPN) structure with enhanced bottom-up path, which improves the propagation of low-level features. At the same time, adaptive feature pooling, which links feature grid and all feature levels, is used to make useful information in each feature level propagate directly to following subnetwork.
- **Head: Yolo layer. G**enerateing 3 different sizes (18× 18, 36× 36, 72× 72) of feature maps to achieve multi-scale prediction, enabling the model to handle small, medium, and big objects. Multi-scale detection ensures that the model can follow size changes in the process of fire evolution.

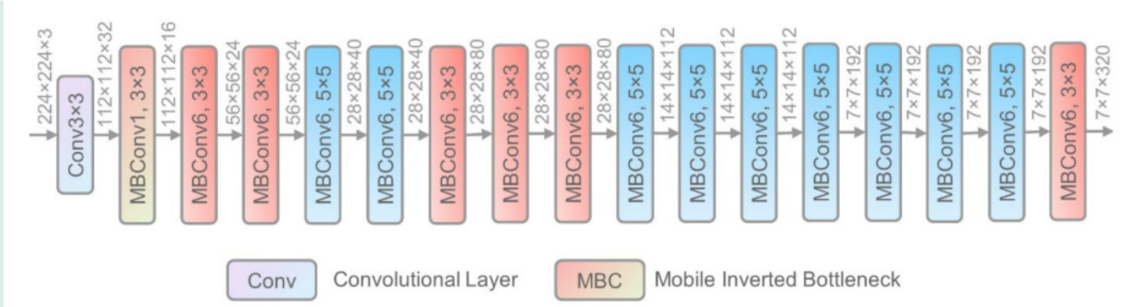
▼ EfficientDet



- EfficientDet employed state-of-the-art network **EfficientNet** as its backbone, making that the model has sufficient ability to learn the complex feature of diverse forest fires.
- It applied an improved PANet, named bi-directional feature pyramid network (**Bi-FPN**) as its neck, to allow easy and fast multi-scale **feature fusion**. Bi-FPN introduces learnable weights, enabling network to learn the importance of different input features, and repeatedly applies top-down and bottom-up multi-scale feature fusion.
- It integrates a compound scaling method that uniformly scales the resolution, depth, and width for all backbone, feature network, and box/class prediction networks at the same time, which ensures the maximum accuracy and efficiency under the limited computing resources.

▼ EfficientNet

It applied a novel model scaling strategy, namely compound scaling method, to balance network depth, network width, and image resolution for **better accuracy at a fixed resource budget**.



Evaluation metrics

Frame accuracy (**FA**) and false positive rate (**FPR**).

For one image, if the detector misses any fire object, we call it is a frame false (**FF**), otherwise frame true (**FT**).

If the detector treats any fire-like object as fire, we call it is a false positive (**FP**), otherwise true positive (**TP**).

$$FA = \frac{FT}{FT + FF} * 100$$

$$FPR = \frac{FP}{FP + TP} * 100$$

Table 1. Microsoft COCO criteria—commonly used in object detection task for evaluating the model precision and recall across multiple scales.

Average Precision (AP)	
$AP_{0.5}$	AP at IoU = 0.5
AP Across Scales:	
AP_S	$AP_{0.5}$ for small objects: area $< 32^2$
AP_M	$AP_{0.5}$ for medium objects: $32^2 <$ area $< 96^2$
AP_L	$AP_{0.5}$ for big objects: area $> 96^2$
Average Recall (AR)	
$AR_{0.5}$	AR at IoU = 0.5
AR Across Scales:	
AR_S	$AR_{0.5}$ for small objects: area $< 32^2$
AR_M	$AR_{0.5}$ for medium objects: $32^2 <$ area $< 96^2$
AR_L	$AR_{0.5}$ for big objects: area $> 96^2$

Experiment

1. Yolov5 and EfficientDet, are trained with 2381 forest fire images, and tested with 476 forest fire images.
2. EfficientNet is trained with 2381 forest fire images and 5804 non-fire images, and tested with 476 forest fire images and 1160 non-fire images.
3. Pytorch, NVIDIA GTX 2080Ti.

Model	Train	Test	Optimizer	LR	Batch Size	Epoch
Yolov5	2381	476	SGD [41,42]	1×10^{-2}	8	300
EfficientDet	2381	476	AdamW [43]	1×10^{-4}	4	300
EfficientNet	8185	1636	SGD	1×10^{-2}	8	300

LR: learning rate, SGD: stochastic gradient descent, AdamW: Adam with decoupled weight decay.

Model	$AP_{0.5}$	AP_S	AP_M	AP_L	$AR_{0.5}$	AR_S	AR_M	AR_L	FPR	FA	Latency (ms)
SSD	66.8	37.8	42.4	78.6	70.1	39.1	45.7	82.7	45.6	92.6	88.8
Yolov3	66.4	26.0	44.6	78.1	71.1	26.1	52.5	82.5	22.9	88.0	**15.6**
Yolov3-SPP	68.3	56.3	49.9	76.7	73.9	60.9	56.6	81.9	30.7	93.3	**15.6**
Yolov4	69.6	53.7	48.9	78.4	75.5	60.9	57.5	83.9	61.9	94.1	20.5
Yolov5	70.5	51.9	53.7	79.2	75.6	56.5	61.2	83.0	22.6	94.7	28.0
EfficientDet	75.7	63.7	58.5	83.0	79.2	65.2	63.9	86.5	41.8	95.5	65.6
Ours (2 learners)	**79.7**	**72.2**	**65.6**	**85.5**	**84.1**	**76.1**	**73.1**	**89.3**	51.6	**99.4**	66.8
Ours (3 learners)	79.0	**72.2**	64.9	84.7	83.8	**76.1**	72.6	88.9	**0.3**	98.9	66.8

Note that $AP_{0.5}$, AP_S, AP_M, AP_L, $AR_{0.5}$, AR_S, AR_M, AR_L, FPR, and FA are all percentages. The best figure of each metric are highlighted in bold.

Further improvement

1. labeling strategy for forest fires
2. investigate the network architecture of backbones
3. develop a forest fire tracking system

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  title={A Forest Fire Detection System Based on Ensemble Learning},
  author={Xu, Renjie and Lin, Haifeng and Lu, Kangjie and Cao, Lin and Liu, Yunfei},
  journal={Forests},
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