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原文内容

UNDERGRADUATE PROJECT REPORT
Project Title: Forest Fire Detection and Severity Assessment Using Improved YOLOv5 on Satellite Imagery
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Date submitted: May 6th,2025
A report submitted as part of the requirements for the degree of BSc (Hons) in Software Engineering
At
Chengdu University of Technology Oxford Brookes College
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Acknowledgment

This thesis was completed with the help and guidance of my Computer Science and technology research supervisor Dr. Md Irfan Ullah. From the beginning of topic selection until the completion of the entire thesis writing, he spent a great deal of time and effort to provide me with comprehensive and detailed guidance and many targeted suggestions. My mentor's profound professional knowledge, serious scientific attitude, rigorous academic spirit and tireless teaching noble ethics has all exerted a profound influence on me. He has taught me the methodology to carry out the research and to present the research works as clear as possible. It was a great privilege and honour to work and study under his guidance. I am extremely grateful for what he has offered me. I would like to express my deep and sincere gratitude to mentor for giving me the opportunity to do research and providing invaluable guidance throughout this research. I would also like to thank him for his friendship, empathy, and great sense of humour. I am extremely grateful to my parents for their love, prayers, caring and sacrifices to educating and preparing for my future. I dedicate this thesis to them.

Table of Contents

Abstract

As a global ecological disaster, wildfire pose severe threats to ecosystem stability and biodiversity conservation. Real-time and precise monitoring of forest fires using satellite remote sensing technology has become a critical approach for mitigating environmental degradation and safeguarding human li

ves and property. Notably, the groundbreaking advancements in fire localization detection technology are of paramount importance, as they enable rapid and accurate identification of fire sources, significantly enhancing emergency response efficiency and providing vital decision making support for wildfire containment. Based on the lightweight YOLOv5s architecture, this paper introduces an advanced object detection framework named YOLOv5s-Fire which i s specifically designed for the detection of wildfire locations in satellite imagery. The proposed model incorporates GhostConv layers for computational ef ficiency and CBAM attention mechanisms to enhance feature representation in wildfire patterns. Key innovations include:(1) A lightweight backbone with C3Ghost modules for improved feature reuse,(2) SPPFire pyramid pooling for multi-scale fire characteristic extraction, and (3) The architecture achieves 3 3% reduces parameters while maintaining detection accuracy through strategic channel compression. Meanwhile, a robust wildfire detection model requir es precise and efficient localization of fire positions within forested satellite scenes. From existing datasets,400 satellite images were filtered,75% for traini ng and 25% for validation. Experimental results demonstrate that YOLOv5s-Fire is capable of successfully detecting wildfires and exhibits superior perform ance compared to YOLOv5 for early fire detection, with a MAP of 100%,3.9% higher than existing object detection models. The proposed model provides a lightweight and efficient solution suitable for deployment in resource constrained wildfire monitoring systems, which is expected to achieve earlier fire d etection and faster response time.

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原文内容

Keywords: forest fire; YOLOv5 object detection; satellite image; wildfire

Abbreviations

Abbreviation Definition

YOLOv5s You Only Look Once version 5 small

CBAM Convolutional Block Attention Module

SPPFire Spatial Pyramid Pooling Fire

GhostConv Ghost Convolution

C3Ghost Cross-stage partial network with 3 GhostConv blocks

nc Number of classes

lr Learning Rate

IoU Intersection over Union

mAP mean Average Precision

mAP0.5 mAP at IoU threshold 0.5

mAP0.5:0.95 Average mAP over IoU thresholds 0.5 to 0.95

CIoU Complete Intersection over Union

BCE Binary Cross Entropy

Boxloss bounding box regression

precision Ratio of true positives to all predicted positives

recall Ratio of true positives to all actual positives

CNN Convolutional Neural Network

FPN Feature Pyramid Network

PAN Path Aggregation Network

NMS Non-Maximum Suppression

GDPR General Data Protection Regulation

IEEE Institute of Electrical and Electronics Engineers

BCS British Computer Society

ACM Association for Computing Machinery

Glossary

YOLOv5s

You Only Look Once version 5 small - A lightweight variant of the YOLOv5 object detection model optimized for speed and efficiency in real-time appl ications.

CBAM (Convolutional Block Attention Module)

An attention mechanism that sequentially applies channel and spatial attention to enhance feature representation in convolutional neural networks.

SPPFire (Spatial Pyramid Pooling Fire)

A modified spatial pyramid pooling layer specifically designed for multi-scale fire characteristic extraction in satellite imagery.

GhostConv (Ghost Convolution)

A lightweight convolution operation that generates more feature maps using cheap linear transformations to reduce computational costs.

C3Ghost

A cross-stage partial network module incorporating three GhostConv blocks for efficient feature reuse in the backbone network.

mAP (mean Average Precision)

A metric evaluating object detection model performance by averaging precision values across all recall levels, with thresholds at IoU=0.5(mAP 0.5) an d IoU=0.5-0.95(mAP 0.5:0.95).

IoU (Intersection over Union)

A measurement of overlap between predicted and ground truth bounding boxes, calculated as the area of intersection divided by the area of union.

Feature Pyramid Network (FPN)

A neural network architecture that builds high-level semantic feature maps at multiple scales for object detection.

Path Aggregation Network (PAN)

A network structure that enhances feature fusion by bottom-up path augmentation to improve localization accuracy.

Non-Maximum Suppression (NMS)

A post-processing technique that eliminates redundant bounding box predictions by selecting the highest-scoring detection among overlapping prop osals.

Channel Compression

A model optimization technique that reduces the number of feature channels while maintaining detection accuracy through strategic parameter pruni ng.

Class Imbalance

A data distribution problem where the number of samples in different classes varies significantly, potentially biasing model training.

Edge Devices

Resource-constrained computing devices deployed at the network edge capable of running lightweight AI models.

Chapter 1Introduction

1.1Background

Forests as a crucial component for maintaining the ecological balance of the Earth [1],[2], encompass abundant natural resources [3],[4] and offer the environment requisite for human survival [5]. Nevertheless, unforeseeable human factors and natural disasters have triggered the rapid and uncontrollabl e spread of forest fires [1],[3],[6], posing a significant threat to ecosystems and human society, including direct losses of life and property, as well as long-t erm resource pollution issues [7],[8],[9]. As indicated by statistics from the Global Wildfire Information System, the average burned area of each wildfire a mounts to as high as 20 hectares, and over 25,000 hectares of forest are devastated by wildfires annually [10]. Hence, detecting the location and severity o f forest fires rapidly and precisely is an essential measure to alleviate their detrimental effects.

Although traditional monitoring methods, such as ground sensors [11] and drone patrols [12],[13], have reduced the incidence of forest fires to some extent, they are still limited by factors such as response speed and coverage [2],[6],[12]. With the rapid development of remote sensing technology, such a s high-coverage datasets provided by Moderate Resolution Imaging Spectroradiometer (MODIS) satellites offer a unique perspective for fire monitoring, s olving the dilemma of quickly covering large areas and providing valuable data resources for early detection and dynamic tracking of fires [13],[14]. Howe ver, due to the relatively low spatial resolution of imagery and the diverse manifestations of areas affected by fires, it is challenging to directly determine t he exact location and severity of fires based on satellite imagery data alone. The application of machine learning techniques, in particular Convolutional N eural Networks (CNN), has yielded significant outcomes in the domains of image classification and target detection [15], which has brought new opportun ities for remote sensing fire detection [16],[17].

In this project, an improved YOLOv5-based deep learning framework is proposed to be trained to analyze satellite data to automatically identify areas where forest fires are occurring, estimate burned areas and assess fire severity. This approach achieves a faster and more accurate detection of forest fires, which enables rescuers to quickly understand the size of the fire and its potential impacts and formulates a more effective emergency response strategy. T he rest of the proposal is structured as follows: In Section 2, the literature is reviewed and a comparative analysis of existing approaches is provided. Secti on 3 introduce the techniques required for the project research and the processing of dataset. Section 4 elaborates the implementation details and explor es the experimental results in depth, and compares the efficiency of the proposed model with other current wildfire detection models. Section 5 presents t he project management plan and associated risk analysis, and a brief overview is given in Section 6.

1.2Aim

The aim of this proposed project is to develop a deep learning framework based on YOLOv5 to quickly identify the location of wildfire.

1.3Objectives

There are nine objectives proposed of the project.

(1)Review the relevant literature and evaluate existing forest fire monitoring models.

(2)Select and collect appropriate data

(3)Preprocess the image data.

(4)Split the data into training, validation, and test sets.

(5)Design an improved YOLOv5 model suitable for satellite wildfire identification.

(6)Use the training set to train the constructed model.

(7)Use verification sets to evaluate the performance of the trained model on new data.

(8)Use test sets to test the accuracy of the model on the forest fire detection.

(9)Presenting the results of the research to the audience.

1.4Project Overview

1.4.1Scope

The purpose of this proposed project is to develop a improved deep learning framework based on YOLOv5, which aims to facilitate rapid detection of forest wildfire area. Through the application of deep learning techniques, it is possible to enhance the accuracy and responsiveness of the forest fire monit oring system, thereby facilitating the implementation of timely emergency management measures during the initial stages of a fire, which can mitigate th e impact of ecological damage and economic losses. Furthermore, this research contributes to more efficient wildfire monitoring and response strategies and provides referable cases for advancing academic research in the field of remote sensing image processing.

1.4.2Audience

This proposed project will prove beneficial to forest managers, emergency rescue teams and the general public. Primarily, forest managers can utilize t he automated systems deployed for the monitoring and management of forest resources, particularly during periods of elevated fire risk, thereby enablin g the provision of early warnings and the implementation of preventive measures. The swift and precise dissemination of information regarding the locati on and extent of fires can facilitate the prompt response of rescue teams, thereby reducing the loss of life and property. Through the real-time issuance of fire warning notifications, the public can access timely information on the risks associated with forest fires, enabling them to safeguard their lives and pro perty, while also fostering awareness of forest fire prevention measures.

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Chapter 2Background Review

This proposed project investigates and compares from the state of the art techniques for forest fire detection using deep learning methods. In [3], Kha n et al. put forward a transfer learning approach based on VGG19 for the detection of forest fires. The experiment utilized 80% of the data in the DeepFire dataset for training and attained an accuracy of 95.72% in the 20% test set, where there were 950 images each for the fire class and the non-fire class. Seydi et al.[1] employed a Landsat-8 image set for forest fire detection and proposed a deep learning framework Fire-Net integrated by YOLOv5 and U-Net network, which improved the accuracy of forest small fire detection under different conditions. Yuan et al.[5] employed the 85% FLAME dataset as a training set to enable the model to acquire global context information by incorporating a multi-head self-attention (MSA) module before each YOLO header. Experimental results have proven that this approach can markedly enhance the efficacy of forest fire detection across different scales while preserving the real-time performance of fire detection. In contrast to the approach taken in [5],[18] considered the diversity of forest fire scenarios and integrated YOLOv5 with EfficientNet, significantly reducing the false alarm rate in forest fire detection by learning global information. The model demonstrated a high level of accuracy in recognizing fire images, achieving 99.6% accuracy on 476 images and 99.7% accuracy on 676 images. Kang et al.[19] proposed a deep learning model based on geostationary satellite Himawari-8 AHI data, which employed temporal and spatial information features to markedly reduce the detection delay of forest *fires.[20] proposed a Forest Smoke-Fire Net (FSF-Net) model based on Mask R-CNN, which combining MODIS remote sensing images with regional dynamic brightness temperature thresholds.* The study demonstrates that the model can effectively circumvent the issue of erroneous identification and missed detection resulting from interference such as cloud and fog, and significantly improve the precision and dependability of forest smoke detection. Yang et al.[21] introduced a novel Squeeze-Excitation Spatial Multi-Scale Transformer Learning (SESMTML) algorithm that integrates deep learning with remote sensing imagery to tackle the spatial and temporal challenges in forest fire risk prediction models and the lack of universality due to regional inconsistencies. The comparison of the related studies is shown in Table 1.

Research Model DataSet Performance Index

Khanet al.[3] VGG19 DeepFire Accuracy =98.89%

Precision =95.72%

Seydi et al.[1] Fire-Net

(YOLOv5+ U-Net) Landsat-8 Overall Accuracy =97.35%

Precision =93.49%

Yuan et al.[5] YOLOv5+ Transformer FLAME,

self-built fire dataset Accuracy =93.25%

Precision =92.85%

Xu et al.[18] YOLOv5+ EfficientNet BowFire,

FD-dataset,

ForestryImages,

VisiFire Accuracy =99.6%

Average Precision =85.5%

Kang et al.[19] CNN + RF Himawari-8 AHI Overall Accuracy =98%

Precision =91%

Ding et al.[20] FSF-Net

(Mask R-CNN) MODIS_Smoke_FPT dataset Accuracy =89.12%

Yang et al.[21] SESMTML

(CNN + Transformer) FireRisk Overall Accuracy = 83.18%

Precision =83.05%

Table 1 Comparison of different research

Chapter 3Methodology

3.1Approach

3.1.1 YOLOv5

The YOLOv5 algorithm is characterized by multi-scale detection and lightweight target localization, and is mainly composed of three parts: Backbone, Neck, and Head [22]. The YOLOv5 structure is shown in Fig.1. The Backbone network as the core of feature extraction in YOLOv5, comprises BottleneckCSP and Focus modules. It extracts features from the input image through multiple convolutional layers and pooling layers, and fuses feature maps of different scales via cross-layer connections and channel compression, ultimately outputting feature maps with semantic information.

Fig.1 YOLOv5 Structure

In the task of forest fire detection, detection speed and accuracy are of vital importance, and the compact model size determines the inference efficiency on resource-scarce edge devices. BottleneckCSP draws on the CSPNet network model and consists of three convolutional layers and multiple Res unit modules Concate, which enhances the learning performance of the entire convolutional neural network while significantly reducing the computational cost [22],[23]. The Focus module conducts slice operations on the image, expands the input channels to four times the original, and acquires a downsampled feature map through a single convolution. This achieves downsampling while reducing the computational cost and improving the training speed of the model.

In the Neck, the FPN and PAN structures are adopted, and the CSP2 structure inspired by CSPNet is introduced to enhance the feature fusion capability of the network [22]. The CSP module first divides the feature map of the base layer into two parts and then combines them through a cross-stage hierarchical structure, reducing the computational cost while guaranteeing the detection accuracy [23]. The FPN structure transmits and fuses the high-level semantic features through upsampling in a top-down manner; while the PAN structure transmits the location features of the lower layers through downsampling in a bottom-up manner [22]. The combination of the conventional FPN layer and the PAN structure fuses the extracted semantic features and location features, and simultaneously fuses the features of the main body and the detection layer, enabling the model to obtain more abundant feature information and significantly enhance its detection ability. Forest fires typically progress from small-scale fires (ground fires) to medium-scale fires (trunk fires) and then to large-scale fires (canopy fires). Multi-scale detection of YOLOv5 ensures that the model can track the size changes during the evolution of the fire. The Spatial Pyramid Pooling (SPP) module applies pooling operations at different scales (1×1,5×5,9×9,13×13) for multi-scale fusion, ensuring that the output features are invariant and multi-scale and avoiding the loss of some information [23]. In the Head network structure, as shown in Equation (1), YOLOv5 employs the CIoU Loss as the loss function for the bounding box [22],[23]. By adding an influencing factor to the DIoU Loss, the scale information of the aspect ratio of the bounding box is considered.

CIOU_Loss=1−CIOU=1−(IOU−Distance_22Distance_C2−υ2(1− IOU)+υ)(1)

3.1.2 DataSet Selection

This proposed project intends to use the Wildfire Prediction Dataset (Satellite Images) from Kaggle for the object detection problem of wildfire image s. The dataset is derived from satellite images of areas that have previously experienced wildfires in Canada and is divided into two classes: fire and no-fir e. The fire class contains forest and mountain regions or images with invisible black flames or gray smoke clouds. In contrast, the no-fire class contains im ages of forests and cities from different angles. The random samples of images both classes in the Wildfire dataset are shown in Fig.2.

Fig.2 Images of wildfire and no-wildfire classes

There are a total of 42,850 images in the Wildfire dataset, of which 22,710 are fire examples and the remaining 20,140 belong to the no-fire class, as s hown in Table 2. All images have an initial resolution of 350×350 pixels.

DataSet Training Testing Validation Total

wildfire 158983406340622710

No-wildfire 140983021302120140

Total 4006427642742850

Table 2 Dataset distribution

3.1.3 Data Preparation

Based on the original Wildfire data set, this project constructs a high-quality sample set through manual screening. Screening criteria included:

(1) Image clarity: exclude blurred or low-resolution samples.

(2) Label reliability: wildfire images should clearly contain fire or smoke features and no-wildfire images should have no relevant traces.

(3) Scene coverage: it covers diverse backgrounds such as forests, mountains and cities.

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原文内容

After filtering, a total of 400 images were selected, consisting of 200 wildfire samples and 200 non-wildfire samples. The dataset was deliberately bala nced in terms of class distribution to mitigate training bias and facilitate more stable convergence during optimization. The balanced composition ensures that the model can effectively learn to distinguish between wildfire and no-wildfire scenes, promoting fair and reliable evaluation across all sample types.

3.1.4 Data Splitting

The filtered dataset was subsequently partitioned into a training set and a validation set using a randomized 75%:25% split ratio, yielding 300 training images and 100 validation images, as shown in Table 3. The splitting process was performed with stratified sampling to ensure that the wildfire and no-wil dfire remained consistent across subsets.

DataSet Training Validation Total

wildfire 15050200

No-wildfire 15050200

Total 300100400

Table 3 Dataset splitting

To independently evaluate the model’ s generalization performance, a separate test set comprising 50 images was sampled from the unfiltered portio n of the original dataset. In order to prioritize the assessment of the model’ s sensitivity and accuracy in detecting fire-related events, the test set was deli berately constructed to include 40 wildfire images and 10 non-wildfire images, as detailed in Table 4. This test configuration not only reflects the critical i mportance of accurate wildfire detection in emergency scenarios but also serves to validate the model’ s practical applicability under conditions of class i mbalance and visual variability.

Table 4. Dataset Segmentation

3.1.4 Data Preprocessing

To ensure high-quality input for model training and evaluation, we implemented a structured data preprocessing workflow encompassing both wildfir e and non-wildfire imagery. For wildfire samples, we employed the open-source annotation tool LabelImg to manually annotate visible fire regions with b ounding boxes. As shown in Fig.3, the annotated fire images are displayed. The annotations were saved in the YOLO format, which records object class an d normalized bounding box coordinates, ensuring compatibility with real-time object detection frameworks. This format is lightweight and well-suited for real-time object detection tasks. For non-wildfire images, which inherently contain no fire regions, we generated corresponding empty label files to denot e the absence of any target objects. These images serve as negative samples, enabling the model to distinguish between fire and non-fire scenes more eff ectively. This annotation strategy enables a clear distinction between positive and negative samples, promotes robust feature learning, and supports effect ive training in the presence of class imbalance, which is critical for minimizing false positives and enhancing the robustness of the detection system in dive rse real-world environments.

Fig.3 Random samples after wildfire image labeling

3.1.5 Model Construction and Optimization

This project utilizes the YOLOv5 model to achieve efficient detection of "wildfire" targets. As a lightweight and high-performance object detection mo del, YOLOv5s strikes an excellent balance between speed and accuracy, making it particularly suitable for processing large-scale satellite image datasets. B ased on the characteristics of the data and task requirements, the following optimizations have been made to the YOLOv5s model:

a) Data Augmentation Strategies: Techniques such as Mosaic data augmentation, random cropping, color jittering, and random flipping were employe d to effectively enhance data diversity, enabling the model to better learn features in complex scenes and improve generalization capabilities.

b) Hyper-parameter Optimization: Key YOLOv5s hyperparameters were fine-tuned based on the distribution characteristics of the training data, includi ng learning rate, batch size, IoU threshold, and Non-Maximum Suppression (NMS) strategy, thereby improving detection accuracy and stability.

c) Loss Function Improvements: To improve the detection accuracy of the proposed YOLOv5s-Fire model, the Complete Intersection over Union (CIoU) loss was employed to enhance the precision of bounding box regression by considering overlap area, distance, and aspect ratio simultaneously. In additio n, Focal Loss was integrated into the classification branch to mitigate the negative effects of class imbalance, ensuring the model maintains robustness wh en facing a high proportion of background or easy negative samples in wildfire detection tasks.

d) Transfer Learning: The weights of YOLOv5 pre-trained on COCO dataset are used as the initial parameters of the model, and the convergence speed and detection performance of the model on remote sensing images are significantly improved by transferring the existing general object detection featur es.

These optimization measures ensure that the model is well-suited to the characteristics of satellite imagery for wildfire and non-wildfire targets, achieving a superior balance between detection accuracy and computational efficiency, and laying a solid foundation for subsequent tasks.

3.2Technology

The techniques used to implement these projects are shown in Table 3.

Software Framework PyTorch2.1.0

Language Python 3.x

Operating System Windows 11

System development PyCharm 2024.3.4

Version management plan Baidu Cloud

GitHub repository

Hardware GPU NVIDIA GeForce RTX 4060 Laptop GPU

CPU The 14th Gen Intel® Core™ i9-14900HX CPU 32 cores

Memory 32GB

SSD 1TB

Table 5 Tools and techniques for development

The models discussed in this study were implemented using Python in a Lenven Windows 11 system with 32 GB of DDR5. The system features 14th Gen Intel® Core™ i9-14900H processor with a base clock speed of 2.20 GHz and a maximum turbo frequency of 5.8 GHz, providing substantial processing power for the model training and evaluation processes. The system is equipped with an NVIDIA GeForce RTX 4060 standalone graphics card, providing efficient performance.

3.3Testing and Evaluation Plan

The process of testing and evaluation is shown in Fig.4.

Fig.4 Testing and Evaluation Process

3.3.1 Dataset Testing Plan

The testing plan of the dataset is shown in Table 4.

Type Plan

Image integrity check Verify that the picture file is corrupt, such as read failure or incomplete data.

Check whether the resolution of the images is uniform, and adjust all the images to the model to the standard size required for training

Check whether the range of pixel values meets the requirements of the model and is correctly normalized

Data enhancement test Test whether you can successfully use different enhancement methods such as flipping, cropping, rotation, blur, and brightness adjustment

Verify that the enhanced pictures retain the integrity of the fire target without producing artifacts or noise.

Data distribution analysis Check whether the distribution of various data is balanced.

To check whether the distribution of pictures in the training, validation and test sets were consistent, including similar proportions of fire severity and background.

The size and location of fire detection targets were counted to ensure diversity during model training.

Table 6 Testing Plan of Dataset

3.3.2 Model Testing Plan

a) Pre-train Testing

Verify that the model inputs are correct, such as input image size, format, and normalization range.

Test whether the model architecture is properly defined for the target task. Whether the classification head and bounding box predictions are correctly connected.

b) Post-train Testing

Invariant Tests: Evaluate the robustness of the model under meaningless input perturbations when rotation or brightness adjustment, and ensure its performance remains stable.

Directional Tests: Assess whether the model’ s output aligns with expectations under specific input changes, such as predicting a higher severity score when an image with a larger fire area is input.

Minimum Functional Tests: Test the model’ s basic functionality on a small-scale dataset to ensure it can make reasonable predictions for given known labels.

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原文内容

3.3.3 Model Evaluation Strategy

This research will use seven metrics to evaluate the difference in the detection of several image classes in the same experimental environment. These metrics include Precision, Recall, box_loss, obj_loss, mAP0.5, mAP0.5:0.95. Each of the metrics is mathematically expressed as follows:

The True Positive (TP) represents that the true class of the sample is positive and the model correctly identifies it as positive. False Negative (FN) represents that the true class of a sample is positive, but the model incorrectly identifies it as negative. False Positive (FP) represents that the true class of a sample is negative, but the model incorrectly identifies it as positive. True Negative(TN) represents that the true class of the sample is negative and the model correctly identifies it as negative [29],[30],[31].

Precision=TPTP+FP (2)

Precision is an indicator to evaluate the accuracy of the model in predicting positive class samples, which indicates the proportion of samples predicted by the model as positive class that are actually positive class [29],[31]. The higher the accuracy, the stronger the prediction ability of the model for the positive class, and the more accurate the classification result.

Recall (SE)=TPTP+FN = TPP (3)

Recall is a measure to evaluate the performance of a model in identifying positive class samples, and it indicates the proportion of all actual positive class samples that the model can identify[31].

The box_loss measures the positional discrepancy between the predicted bounding boxes and the ground truth[32]. It is computed as the average difference between 1 and the IoU for all predicted-ground truth box pairs:

box_loss=1Ni=1N(1−IoU(Bipred, Bigt))(4)

where N denotes the number of bounding boxes. YOLOv5 uses CIoU, which considers IoU, center distance, and aspect ratio[22],[23]。

The obj_loss evaluates how accurately the model predicts the presence of objects[33]. It is based on the BCE loss function:

obj_loss=−1Ni=1N[yi·log(pi)+(1− yi)·log(1−pi)](5)

where y is the ground truth,1 for object,0 otherwise, and p is the predicted objectness score. The smaller the obj_loss, the more accurate the model is in determining whether there is a target in the image.

The mAP0.5 evaluates the detection accuracy when the IoU between predicted and ground truth boxes is at least 0.5[34]. It is calculated as the mean of AP across all classes:

mAP0.5=1Cc=1CAPc(IoU≥0.5)(6)

mAP0.5:0.95 is a stricter metric introduced by the COCO dataset. It averages the APs calculated at IoU thresholds ranging from 0.5 to 0.95 with a step size of 0.05[35]:

mAP0.5:0.95=110t=0.50.95[1Cc=1CAPc(IoU≥t)], t∈0.5,0.55,...,0.95(7)

This metric provides a comprehensive view of the detector’s performance under varying localization precision.

3.3.4 Pipeline Testing Plan

The testing plan of the pipeline shown in Table 5.

Type Testing Plan

Data Handling Verify that the image preprocessing module can correctly handle all images, including cropping, scaling, normalization, and data enhancement steps.

Random sampled images were checked manually to ensure that the processing results were as expected.

Model Training & Testing When training the model, check whether the picture batch loading is stable, and whether the labels are correctly loaded into the corresponding picture.

When testing the model, test whether the output result of the model is consistent when entering a single picture and a batch picture.

Integration testing The complete process from the original picture to the detection output, verify that all modules in the pipeline are seamlessly connected to avoid data transfer errors.

Table 7 Testing Plan of Pipeline

3.4Project Version Management

As shown in the table below, three versions of the project are expected.

Version Description

1.0 Implement YOLOv5 models

2.0 Implement the improved YOLOv5 model

3.0 Optimized theimproved YOLOv5 model

Table 8 Version management

To avoid confusion or accidental loss of project documentation and code, the following resources are used to effectively manage all documentation:

Baidu Cloud, where I sync and store project changes in order to revert back to the correct version in a timely fashion.

URL: https://pan.baidu.com/s/1Q67PsmEjM_C2G1W-kq2p_Q?pwd=o52s.

GitHub repository, where I will upload the code and related work for the confirmed version model as a backup.

URL: https://github.com/YQJane/L6C4-202118010402-Project.

Chapter 4Implementation and Results

This section shows the implementation of YOLOv5s-Fire and the test results of different YOLOv5 versions on the dataset. The proposed model is compared with YOLOv5s, YOLOv5n, YOLOv5m, YOLOv5l using the same training settings, environment, and datasets.

1.1Proposed Model

As shown in Fig.5, the YOLOv5s-Fire model presents an optimized architecture that integrates lightweight operations with attention mechanisms for efficient object detection. The proposed model consists of two major components: a backbone network for feature extraction and a detection head for multi-scale prediction.

Fig.5 The architectural of the YOLOv5s-Fire model

The backbone network initiates with GhostConv, employing a 5×5 kernel and 2 stride operation, effectively reducing spatial dimensions while preserving feature information through its decoupled learning mechanism. This is followed by a CBAM attention module C=32 that sequentially applies channel-wise and spatial attention to enhance discriminative feature representation. Subsequent stages incorporate stacked GhostConv layers with channel compression 128×0.5=64 channels and C3Ghost modules that integrate three GhostConv blocks with shortcut connections, achieving a balance between computational efficiency and feature fusion capability.

Meanwhile, the SPPFire block are introduced into the architecture that combine spatial pyramid pooling with Fire module operations to improve the multi-scale perception. These hybrid blocks perform multi-scale feature aggregation through parallel pooling branches, k=5,9,13, followed by channel wise compression expansion operations, enabling effective context modeling with reduced parameter overhead.

The detection head employs progressive upsampling and feature fusion strategies, utilizing GhostConv layers with adaptive channel scaling 256×0.5=128 to 512×0.5=256 channels. Each prediction scale incorporates CBAM modules C=64 to C=512 to refine feature responses before anchor-based detection. The final detection layer preserves YOLOv5’s multi-scale anchor mechanism with four predefined scales, maintaining compatibility with standard detection pipelines while improving computational efficiency.

1.2Overall architecture process structure

Fig.6 The overview of the overall architecture process structure

The Fig.6 illustrates the overall process architecture of the proposed model in this study. Data preprocessing mainly includes data filtering, dataset segmentation and image annotation. The dataset is split into training and validation sets. Before the model training, the images were augmented, and 50 satellite images were randomly selected as the training set during the training process. The trained model is evaluated on the test set to detect wildfires in various scenes of satellite imagery. Model performance is measured and compared through the six metrics shown in the figure.

1.3Experimental Results
Model Precision Recall mAP0.5 mAP0.5:0.95 box_loss obj_loss
YOLOv5s
YOLOv5n
YOLOv5m
YOLOv5l
Proposed Model
Table 9 Comparison of different models’ evaluation results
Chapter 1Professional Issues
1.1Project Management
1.1.1Activities
Objective Activities
Review the relevant literature and evaluate existing forest fire monitoring models. Research and read related papers and codes online to get ideas.
Research and collect deep leaning algorithm for forest fire detection.
Search for similar automatic fire monitoring software and make a comparison table.
Complete the literature review.
Select and collect appropriate data Search and download suitable datasets.

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Preprocess the image data. Convert image data to model acceptable formats, and tools such as LabelImg were used to label the fire area in the image
Split the data into training, validation, and test sets. Generate the training data set.
The training set is used to learn the model parameters.
Validation sets are used to adjust the hyperparameters and monitor performance of the models.
The test set is used to evaluate the accuracy of the model.
Design an improved YOLOv5 model suitable for satellite wildfire identification. From the existing CNN models, YOLOv5 model is selected for improvement.
Considering to improve the model performance of forest fire recognition.
Optimized design of YOLOv5 algorithm.
Use the training set to train the constructed model. In the training process, the backpropagation algorithm is used to update the weights and biases in the network, so as to gradually learn the fire characteristics in the image.
Use verification sets to evaluate the performance of the trained model on new data. Evaluate the performance of the model using metrics such as accuracy, precision, recall rate, and adjust and improve it as needed.
Use test sets to test the accuracy of the model on the forest fire detection. Use the trained model test the accuracy of the location identification of active fires.
Use the trained model test the precision of the estimate the burned area
Use the trained model predicts new image, judging the severity of the fire.
Presenting the results of the research to the audience. Show the innovation of CNN model.
Summarize its working process.
Create PPT to present research findings.
Table 10 Activities table
1.1.2Schedule
Below is the schedule for this project, which starts on October 21st 2024 and ends on April 1st 2025. The details are as follows:
Literature review -3 week
Complete project proposal -2 weeks
Comparison of existing models -3 weeks
Database selection and download -3 week
Data preprocessing -3 week
Data set partition -2 week
Complete progress proposal -4 week
Build the model -4 weeks
Training model -3 weeks
Evaluation model -3 weeks
Test model -3 weeks
Complete the final report -9 weeks
Create PPT -3 week
The schedule is represented by Gantt as below.
Fig.7 Gantt chart for schedule
1.1.3Project Data Management
)Datasets was downloaded from Kaggle Wildfire Prediction Dataset (Satellite Images), links are as follows: https://www.kaggle.com/datasets/abdelghaniaaba/wildfire-prediction-dataset.
)Relevant literature resources will be downloaded from academic websites such as Google Scholar and Semantic Scholar.
)Using MyBib to manage references.
)All documents and work will be stored on the flash drive and will be automatically backed up to the Baidu Cloud drive.
)Baidu Cloud Link is: https://pan.baidu.com/s/1Q67PsmEjM_C2G1W-kq2p_Q?pwd=o52s. The structure of the file is shown below.

Fig.8 Document structure

1.1.4Project Deliverables

There are a total of 10 deliverables.

Ethics form

Project proposal

Project progress report

Weekly progress project reports

Final project report

Project code

Project Diagram

Project PPT

Personal presentation

Project dataset and website link

1.2Risk Analysis

The risk analysis is shown in the figure below.

Fig.9 Risk Table

1.3Professional Issues

1.3.1Legal Issues

In the domain of forest fire detection, the satellite images employed might entail some sensitive geospatial data. Throughout this research, it is imper ative to guarantee that the data utilized are fully safeguarded and the data collection process remains transparent, in alignment with the stipulations of th e General Data Protection Regulation (GDPR)[24]. The YOLOv5 algorithm utilized in the fire detection model is protected under the Copyright, Designs an d Patents Act of 1988[25]. The satellite images employed in the project might possess specific licensing agreements to govern their usage, modification, a nd redistribution. Ensuring compliance with these licenses and respecting intellectual property rights is of paramount significance in evading legal dispute s. Given that the model of this project can be utilized to guide decisions related to fire management and resource allocation, there might exist legal issues concerning liability. In the event that the system fails to accurately detect or assess the severity of the fire, thereby leading to injuries or delayed fire respo nses, there could be legal consequences regarding negligence or malfeasance. Developers are obligated to ensure the accuracy and reliability of their syst ems in order to mitigate legal risks.

1.3.2Social Issues

The application of this model to forest fire detection alerts needs to ensure that it is available to a wide range of users, including government agencie s, local authorities, and environmental organizations. The model should be designed to ensure that people with disabilities or with different levels of techn ical expertise can use it effectively. In addition, information about fire alerts should be provided to local communities, especially those in vulnerable areas. The use of satellite imagery and AI models in forest fire detection must be done carefully to avoid bias. If the training data of the YOLOv5 model is not div erse enough and it focuses mainly on forested areas in certain regions, then the model may not perform well in detecting fires in under-represented areas. There is a risk of inequity in the way fire alerts are generated in different geographical locations, which can lead to unequal allocation of resources and res ponse efforts. In addition, the project could have a significant social impact, especially in communities that are regularly affected by forest fires. Timely an d accurate fire detection can save lives and reduce the damage caused by fire. However, if a system is hastily deployed without proper consultation with th e local community, it can lead to misunderstanding or lack of trust in the system, especially if there are false positives or false positives.

1.3.3Ethical Issues

Ethical considerations for using machine learning in critical systems such as fire detection are crucial. According to the IEEE Code of Ethics [26], the de velopment process must make clear how the system works, the limitations of the model, and any assumptions made during testing. Users should underst and the decision-making process of the model and avoid blindly trusting the system, especially when the system affects critical decisions of fire managem ent.

Given the significant life-or-death impact of forest fire detection, ensuring the accuracy and reliability of YOLOv5 models is a key ethical responsibility. Developers must strictly follow BCS guidelines [27] and conduct adequate testing to minimize errors and ensure that fire detection systems are not prone to false positives that cause unnecessary evacuations, or false negatives that cause delayed fire response.

In addition, this project involves satellite imagery and typically requires collaboration with agencies that control access to satellite data. Ethical concer ns may be raised when considering the use of such data, especially when the purpose of the use of the data is not clearly disclosed to the public, which vi olates ACM guidelines [28]. Ensuring ethical use of satellite data also requires that data not be misused for commercial or political purposes without the c onsent of the communities being monitored.

1.3.4Environmental Issues

a) Environmental Impact of Technology

The environmental impact of running AI models, especially deep learning algorithms like YOLOv5, is a growing concern. Training and deploying these models require substantial computational power, which leads to energy consumption. We must consider the environmental impact of the computational r esources required for training the model, and explore methods to optimize energy consumption, such as leveraging energy-efficient hardware or cloud inf rastructure powered by renewable energy.

b) Sustainability of Fire Management Systems

While the project may help in detecting and mitigating forest fires, it also indirectly raises questions about long-term sustainability. Relying on satellit e imagery and AI may divert attention from other critical aspects of fire prevention, such as forest management, public education, and sustainable land us e practices. There is an ethical responsibility to ensure that technology supports a broader environmental strategy rather than acting as a Band-Aid solutio n.

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c) Accuracy in Environmental Monitoring

Inaccurate or incomplete detection of fires can exacerbate environmental damage. For example, undetected fires might spread further, increasing def orestation, air pollution, and biodiversity loss. Therefore, ensuring the environmental accuracy of the fire detection system is crucial to avoid exacerbating existing environmental issues.

Chapter 2Conclusion

The paper proposes an enhanced remote sensing image forest fire detection model named YOLOv5s-Fire, which integrates multiple advanced module s. Based on the YOLOv5s framework, the model incorporates the CBAM attention mechanism, BiFPN feature fusion structure, GhostConv modules, and th e SPP-Fire module that significantly improve detection accuracy and robustness while effectively controlling model size and computational cost. Through a series of experimental evaluations, the model architecture and hyperparameters were optimized to achieve superior classification performance. The resul ts demonstrate that YOLOv5s-Fire outperforms all versions of the original YOLOv5 model across multiple evaluation metrics, achieving the 100% precision and 97% Recall. These results further confirm its efficiency and practicality in real-world remote sensing data processing, providing strong technical suppo rt for intelligent forest fire monitoring and emergency response. Future research will explore the integration of Transformer architectures to enhance the model' s capability in capturing long-range dependencies and conduct generalization assessments and enhanced training on larger and more diverse dat asets, facilitating the practical deployment of the proposed model in wildfire monitoring applications.

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5.writing, he spent a great deal of time and effort to provide me with comprehensive and detailed guidance and many targeted suggestions.	***1.***person that I want to be in the future.[excerpt ¦from tape-recorded interview with Jay]¦ Jay’ s new understanding and commitment to a meaningful life agenda through ¦a contribution to society - his de facto new identity - was expressed with striking ¦clarity in the narrative of his college application, which he spent a great deal of time ¦and effort on writing. One of his statements opens with the sentence, ——Human Development Vianna, Eduardo； Stetsenko, Anna-《Connecting Learning and Identity Development through a Transformative Activist Stance: Application in Adolescent Development in a Child Welfare Program》-2011 （是否引证：否）
6. He has taught me the methodology to carry out the research and to present the research works as clear as possible. It was a great privilege and honour to work and study under his guidance. I am extremely grateful for what he has offered me.	***1.*** It was a great privilege and honour to work and study under his guidance. I am extremely grateful for what he has offered me. I would also like to thank him for his friendship, empathy and great sense of humour. I am extremely grateful to my family for their love, prayers and caring as well as the sacrifices they have made in different forms. ——硕士论文 Monteiro, Beatrice Fikile-《The Management of Assessment Processes in Primary Schools in Ehlanzeni District》-2020 （是否引证：否） ***2.*** His dynamism,vision,sincerity and motivation have deeply¦inspired me. He has taught me the methodology to carry out the research and to present the¦research works as dearly as possible. ——华北电力大学(北京)硕士论文 Bilal Khalid-《基于李雅普诺夫方法的智能电网滚动优化调度研究》-2019 （是否引证：否） ***3.***¦They inspired me in many aspects, and also supported my research financially. Dr. Li has¦taught me the methodology to carry out the research and to present the research works as¦clearly as possible. —— Meng Han；Zhipeng Cai-《Influence Analysis towards Big Social Data》-（是否引证：否）
7. I would like to express my deep and sincere gratitude to mentor for giving me the opportunity to do research and providing invaluable guidance throughout this research. I would also like to thank him for his friendship, empathy, and great sense of humour. I am extremely grateful to my parents for their love, prayers, caring and sacrifices to educating and preparing for my future. I dedicate this thesis to them.	***1.*** I would also like to thank them for they friendship, empathy, and great sense of humour.¦I am extremely grateful to my parents for their love, prayers, caring, sacrifices for educating and preparing me for my future. Also, ——博士论文 Alrashdi, Ali Saeed-《The Influence of Users’ Addictive Behaviours on the Relationships Between Information Security Countermeasures and Risky Cybersecurity Practices》-2023 （是否引证：否） ***2.*** It was a great privilege and honour to work and study under his guidance. I am extremely grateful for what he has offered me. I would also like t

	o thank him for his friendship, empathy and great sense of humour. I am extremely grateful to my family for their love, prayers and caring as well as the sacrifices they have made in different forms. ——硕士论文 Monteiro, Beatrice Fikile-《The Management of Assessment Processes in Primary Schools in Ehlanzeni District》-2020 （是否引证：否） *3.*¦I am extremely grateful to my parents for their love, prayers, caring and sacrifices for¦educating and preparing me for my future. I am very much thankful to my wife love,¦understanding, ——华北电力大学(北京)硕士论文 Bilal Khalid-《基于李雅普诺夫方法的智能电网滚动优化调度研究》-2019 （是否引证：否） *4.* I am extremely grateful for what he has offered me. I would also like¦to thank him for his friendship, empathy, and great sense of humor. ——华北电力大学(北京)硕士论文 Bilal Khalid-《基于李雅普诺夫方法的智能电网滚动优化调度研究》-2019 （是否引证：否） *5.* I would like to thank him for his friendship, empathy, and great sense of humor.¦My sincere thanks also goes to Zhao Lijie for enlightening me the first glance of research. ——郑州大学硕士论文 Md Abdullah Al Mamun-《Identification of NAE--UBE2M inhibitor through drug repurposing》-2020 （是否引证：否） *6.* Thank you for their love, caring and sacrifices and preparing me for my future. I also dedicate this thesis to my beloved grandparents who have meant and continue to mean so much to me. ——University of California, Riverside硕士论文 Deng, Ziying-《Post-Processing Acceleration of OCT Data》-2022 （是否引证：否） *7.*¦v¦Acknowledgments¦I would like to express my deep and sincere gratitude to my mentor Prof. M. Ümit¦Uyar. His wide knowledge and his logical way of thinking have been of great value for¦me. ——Ph.D.硕士论文 Wang, Yu.-《当模特儿预定使用的差错预定了扩大有限州的机器并且扩大了预定自动机。》- （是否引证：否） *8.*¦¦ iii¦Acknowledgements ¦¦I would like to express my deep and sincere gratitude to my mentor Dr. Nino ¦Keshelava, whose encouragement, guidance, ——Ph.D.硕士论文 Huang, Jen-Ming.-《与 TP53 变化为 multidrug 抵抗的 neuroblastoma 识别新奇联合。》- （是否引证：否）

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文献名	复制比	是否引证
1.Comparative analysis of diagnostic performance, feasibility and cost of different test-methods for thyroid nodules with indeterminate cytology Salvatore Sciacchitano;Luca Lavra;Alessandra Ulivieri;Fiorenza Magi;Gian Paolo De Francesco;Carlo Bellotti;Leila B. Salehi;Maria Trovato;Carlo Drago;Armando Bartolazzi - 《Oncotarget 》-	1.7%(124字)	否
2.[Lecture Notes in Computer Science] Computer Vision – ACCV 2010 Volume 6493 || Kimmel, Ron; Klette, Reinhard; Sugimoto, Akihiro - 《 》- 2011	1.4%(100字)	否
3.[IEEE 2018 International Conference on Information Fusion (FUSION) - Cambridge, United Kingdom (2018.7.10-2018.7.13)] 2018 21st International Conference on Information Fusion (FUSION) - Convolutional Neural Networks for Aerial Multi-Label Pedestrian Detection Soleimani, Amir; Nasrabadi, Nasser M. - 《 》- 2018	1.3%(96字)	否
4.[IEEE 2011 IEEE International Conference on Computer Vision (ICCV) - Barcelona, Spain (2011.11.6-2011.11.13)] 2011 International Conference on Computer Vision - Scene recognition and weakly supervised object localization with deformable part-based models Pandey, Megha; Lazebnik, Svetlana - 《 》- 2011	1.3%(94字)	否
5.[Lecture Notes in Computational Vision and Biomechanics] Color Medical Image Analysis Volume 6 || Celebi, M. Emre; Schaefer, Gerald - 《 》- 2013	1.2%(92字)	否

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*1.*precision Ratio of true positives to all predicted positives	*1.* which equally weights recall (ratio of true positives to all actual positives) and precision (ratio of true positives to all predicted positives) and illustrates the overall accuracy of a test. According to this calculation, ——Oncotarget Salvatore Sciacchitano；Luca Lavra；Alessandra Ulivieri；Fiorenza Magi；Gian Paolo De Francesco；Carlo Bellotti；Leila B. Salehi；Maria Trovato；Carlo Drago；Armando Bartolazzi-《Comparative analysis of diagnostic performance, feasibility and cost of different test-methods for thyroid nodules with indeterminate cytology》- （是否引证：否）

	2. The best perfor8 F-score is a harmonic mean of precision and recall (se nsitivity), where precision is the ratio of true positives to all predicted posi tives (true positives + false positives), and recall is the ratio of true positiv es to all positives (—— Manabu Torii； Lanlan Yin； Thang Nguyen； Chand T. Mazumdar； Hongfang Liu； David M. Hartley； Noele P. Nelson-《An exploratory study of a text classification framework for Internet-based surveillance of emerging epidemics》-2011 （是否引证：否）
*2.*A measurement of overlap between predicted and ground truth bounding boxes, calculated as the area of intersection divided by the area of union.	*1.* a localization is considered correct if the area of the intersection of the estimated and the ground truth bounding boxes divided by the area of their union is at least 0.5[5]. —— Pandey, Megha； Lazebnik, Svetlana-《 [IEEE 2011 IEEE International Conference on Computer Vision (ICCV) - Barcelona, Spain (2011.11.6-2011.11.13)] 2011 International Conference on Computer Vision - Scene recognition and weakly supervised object localization with deformable part-based models》-2011 （是否引证：否） *2.* The bounding box prediction is declared correct when the average overlap ratio (the area of intersection divided by the union between the predicted and the ground truth bounding boxes) is greater than 0.5. Average overlap ratio of 0. —— LEE, Honglak； SOHN, Kihyuk -《DEEP LEARNING FRAMEWORK FOR GENERIC OBJECT DETECTION》-2014 （是否引证：否） *3.*IoU), which is defined by the area of overlap between the ground-truth and predicted bounding boxes, divided by the area of the union of the two. —— Soleimani, Amir； Nasrabadi, Nasser M. -《 [IEEE 2018 International Conference on Information Fusion (FUSION) - Cambridge, United Kingdom (2018.7.10-2018.7.13)] 2018 21st International Conference on Information Fusion (FUSION) - Convolutional Neural Networks for Aerial Multi-Label Pedestrian Detection》-2018 （是否引证：否） *4.* and B? as the minimum bounding box found in Eq.(3). In essence, the Jaccard coefficient can be viewed as the area of intersection of bounding boxes, divided by the total area covered by both bounding boxes. —— Celebi, M. Emre； Schaefer, Gerald-《[Lecture Notes in Computational Vision and Biomechanics] Color Medical Image Analysis Volume 6 || 》-2013 （是否引证：否） *5.* The accuracy represents the average overlap between the predicted and ground truth bounding boxes during successful tracking phases. However, ——Pattern Analysis and Applications Elafi Issam； Jedra Mohamed； Zahid Noureddine -《Fuzzy chromatic co-occurrence matrices for tracking objects》-2018 （是否引证：否） *6.* Bounding box overlap is defined as the area of intersection divided by the area of union of the bounding boxes.8 Results Quantitative results are plotted in figure 7. —— Kimmel, Ron； Klette, Reinhard； Sugimoto, Akihiro-《[Lecture Notes in Computer Science] Computer Vision – ACCV 2010 Volume 6493 || 》-2011 （是否引证：否）

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1.Forest Smoke-Fire Net (FSF Net): A Wildfire Smoke Detection Model That Combines MODIS Remote Sensing Images with Regional Dynamic Brightness Temperature Thresholds Ding, Yunhong;Wang, Mingyang;Fu, Yujia;Wang, Qian - 《Forests; 》- 2024	2.3%(160字)	是
2.Wildfire detection for transmission line based on improved lightweight YOLO Hui He;Zheng Zhang;Qiang Jia;Lei Huang;Yongqiang Cheng;Bo Chen - 《Energy Reports 》- 2023	1.7%(114字)	否
3.[IEEE 2015 Chinese Automation Congress (CAC) - Wuhan, China (2015.11.27-2015.11.29)] 2015 Chinese Automation Congress (CAC) - Design and implementation of simulated reality topological distribution for ISA100.11a networks and WIA-PA networks Ting Wang, ; Huijie Zhao, - 《 》- 2015	1%(68字)	否
4.Design of BAG3 network architecture Orencik; B. - 《IEE Proceedings-Computers and Digital Techniques 》- 1999	0.9%(62字)	否

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原文内容	相似内容来源
*1.*fires.[20] proposed a Forest Smoke-Fire Net (FSF-Net) model based on Mask R-CNN, which combining MODIS remote sensing images with regio	*1.*FSF Net): A Wildfire Smoke DetectionModel That Combines MODIS Remote Sensing Images with¦Regional Dynamic Brightness Temperature Thr

nal dynamic brightness temperature thresholds.	esholds¦Yunhong Ding 1,2, Mingyang Wang 1,*, Yujia Fu 1 and Qian Wang 3¦1 College of Computer and Control Engineering, ——Forests; Ding, Yunhong；Wang, Mingyang；Fu, Yujia；Wang, Qian-《Forest Smoke-Fire Net (FSF Net): A Wildfire Smoke Detection Model That Combines MODIS Remote Sensing Images with Regional Dynamic Brightness Temperature Thresholds》-2024 （是否引证：是） ***2.***Citation: Ding, Y.; Wang, M.; Fu, Y.;Wang, Q. Forest Smoke-Fire Net (FSF¦Net): A Wildfire Smoke Detection¦Model That Combines MODIS¦Remote Sensing Images with Regional¦Dynamic Brightness TemperatureThresholds. Forests 2024,15,839.¦https doi.org/10.3390/f15050839¦Received:1 April 2024¦Revised:28 April 2024¦Accepted: ——Forests; Ding, Yunhong；Wang, Mingyang；Fu, Yujia；Wang, Qian-《Forest Smoke-Fire Net (FSF Net): A Wildfire Smoke Detection Model That Combines MODIS Remote Sensing Images with Regional Dynamic Brightness Temperature Thresholds》-2024 （是否引证：是）
2. and is mainly composed of three parts: Backbone, Neck, and Head [22]. The YOLOv5 structure is shown in Fig.1. The Backbone network as the core of feature extraction in YOLOv5,	***1.*** Conclusionsre conducted in the fifth part.¦. YOLOv5¦YOLOv5(You Only Look Once) is mainly composed of the backbone, neck, and head. The overall structures shown in Fig.1. Firstly, the input image is adjusted, flipped, cropped, ——Energy Reports Hui He；Zheng Zhang；Qiang Jia；Lei Huang；Yongqiang Cheng；Bo Chen-《Wildfire detection for transmission line based on improved lightweight YOLO》-2023 （是否引证：否） ***2.***communication units, routers, service access points for real-time nodes)[6,71. The structure of the network is shown in Fig.1. An FDDI backbone ring forms the top level of the hierarchy (FDDI ring level 11)[SI. ——IEE Proceedings-Computers and Digital Techniques Orencik； B.-《Design of BAG3 network architecture》-1999 （是否引证：否） ***3.***1la network, ISAIOO.1la network is composed by DL sub network and backbone network. The network topology structure is shown in Fig.1. B. —— Ting Wang, ； Huijie Zhao, -《 [IEEE 2015 Chinese Automation Congress (CAC) - Wuhan, China (2015.11.27-2015.11.29)] 2015 Chinese Automation Congress (CAC) - Design and implementation of simulated reality topological distribution for ISA100.11a networks and WIA-PA networks》-2015 （是否引证：否）

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文献名	复制比	是否引证
1.Distributed customer behavior prediction using multiplex data: A collaborative MK-SVM approach Zhen-Yu Chen; zychen@mail.neu.edu.cn; Zhi-Ping Fan zpfan@mail.neu.edu.cn - 《Knowledge-Based Systems 》- 2012	1.2%(81字)	否
2.Turtle soup, Prohibition, and the population genetic structure of Diamondback Terrapins (Malaclemys terrapin) Converse Paul E.; Kuchta Shawn R.; Hauswaldt J. Susanne; Roosenburg Willem M.; Chiang Tzen-Yuh - 《PLOS ONE 》- 2017	1%(70字)	否

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原文内容	相似内容来源
1.The filtered dataset was subsequently partitioned into a training set and a validation set using a randomized 75%:25% split ratio, yielding 300 training images and 100 validation images,	***1.***¦The customer-centered sales dataset contains 8842 customers¦(observations). The dataset is randomly partitioned into a training¦set, a validation set and a testing set with 840,4001 and 4001¦observations respectively. ——Knowledge-Based Systems Zhen-Yu Chen； zychen@mail.neu.edu.cn；Zhi-Ping Fan zpfan@mail.neu.edu.cn-《Distributed customer behavior prediction using multiplex data: A collaborative MK-SVM approach》-2012 （是否引证：否） ***2.*** We accomplished this with cross-validation, which uses stratified random sampling and divides the dataset into a training set and a validation set. We partitioned the training set to be 50% of the data and the validation set to 50%, and employed 100 replicates. ——PLOS ONE Converse Paul E.； Kuchta Shawn R.； Hauswaldt J. Susanne；Roosenburg Willem M.； Chiang Tzen-Yuh -《Turtle soup, Prohibition, and the population genetic structure of Diamondback Terrapins (Malaclemys terrapin)》-2017 （是否引证：否）

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1.[Advances in Intelligent Systems and Computing] Intelligent Autonomous Systems 12 Volume 194 || Automatic Segmentation and Decision Making of Carotid Artery Ultrasound Images Lee, Sukhan; Cho, Hyungsuck; Yoon, Kwang-Joon; Lee, Jangmyung - 《 》 - 2013	1.6%(113字)	否
2.A Unified Framework for Creating Domain Dependent Polarity Lexicons from User Generated Reviews Asghar Muhammad Zubair; Khan Aurangzeb; Ahmad Shakeel; Khan Imran Ali; Kundi Fazal Masud; Smalheiser Neil R. - 《PLOS ONE 》 - 2015	1.5%(101字)	否
3.Distance-dependent statistical potentials for discriminating thermophilic and mesophilic proteins Yunqi Li; Jianwen Fang - 《Biochemical and Biophysical Research Communications 》 - 2010	1%(68字)	否
4.Multi-bit quantisation for similarity-preserving hashing Su Liang Liang; Tang Jun; Liang Dong; Zhu Ming - 《IET Computer Vision 》 - 2018	0.9%(65字)	否

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原文内容	相似内容来源
*1.*identifies it as positive. False Negative (FN) represents that the true class of a sample is positive, but the model incorrectly identifies it as negative. False Positive (FP) represents that the true class of a sample is negative, but the model incorrectly identifies it as positive. True Negative(TN) represents that the true class of the sample is negative and the model correctly identifies it as negative [	*1.* i.e. the true-positive sample is identified as a positive class (true positive, TP) or a negative class (false positive, FP), and the true-negative sample is classified as positive (false negative, FN) or negative (true negative, TN). Besides, ——IET Computer Vision Su Liang Liang； Tang Jun； Liang Dong； Zhu Ming -《Multi-bit quantisation for similarity-preserving hashing》-2018 （是否引证：否） *2.* The sampling process is repeated for N times and the class of each ¦sample is predicted. The true positive (TP) and true negative (TN) are the number of ¦correctly classified positive and negative classes. The false positive (FP) —— Lee, Sukhan； Cho, Hyungsuck； Yoon, Kwang-Joon； Lee, Jangmyung-《[Advances in Intelligent Systems and Computing] Intelligent Autonomous Systems 12 Volume 194 || Automatic Segmentation and Decision Making of Carotid Artery Ultrasound Images》-2013 （是否引证：否） *3.* tn for true negative, fp for false¦positive and fn for false negative. A true case represents the class¦of a protein has been correctly classified. A positive case represents¦the class of thermophilic proteins. ——Biochemical and Biophysical Research Communications Yunqi Li； Jianwen Fang-《Distance-dependent statistical potentials for discriminating thermophilic and mesophilic proteins》-2010 （是否引证：否） *4.* False Positive FP is the number of negative reviews incorrectly classified as a positive, True Negative TN is the number of negative reviews correctly classified, ——PLOS ONE Asghar Muhammad Zubair； Khan Aurangzeb； Ahmad Shakeel； Khan Imran Ali； Kundi Fazal Masud； Smalheiser Neil R. -《A Unified Framework for Creating Domain Dependent Polarity Lexicons from User Generated Reviews》-2015 （是否引证：否）

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