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Smoke-Fire Detection and YOLO (You Only Look Once) - A Review

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Abstract

Yolo's deep learning algorithms make it possible to accurately detect smoke and fire in real time, making it a crucial tool for early fire detection and suppression. This Paper is a survey of the literature on fire detection over the previous three years (2020–2023) using the YOLO (you only look once) algorithm with Attention Mechanism . Due to its widespread use, YOLO has been the primary method of detection in the majority of published works. We have given a thorough review of the application of YOLO in smoke and fire detection in this research by comparing the published works using data sets, methodology, strategies and evaluating performance. To raise the detection rate and decrease the rate of false positives, the majority of works have trained or employed augmentation approaches and an attention model with various Image processing techniques

1. Introduction to YOLO and Fire Detection

YOLO is a real-time object detection algorithm widely used in various applications, including fire and smoke detect–ion. It is a model based on deep learning that identifies things in pictures or videos by using features acquired from a convolutional neural network that is deep (CNN). Real-time applications can benefit from the model's speed and accuracy, which are widely recognized.

In the published articles from 2015–2019, YOLO is directly used for smoke and fire detection in most of the articles. After 2020, all publications focused on improving the detection speed and false positives by improving the old YOLO algorithm, e.g., (H. Xu, Li, and Zhong) (Mukhiddinov, Abdusalomov, and Cho) (Wu et al.) (Xue, H. Lin, and Wang). Some works added an attention model to improve the recognition speed, such as (Bahhar et al.) (Xue, H. Lin, and Wang) (J. Lin, H. Lin, and Wang). Some works used lightweight YOLO models to improve the performance, such as (Wu et al.), and some works incorporated augmentation techniques and shallow neural networks

1.1. Fire and Environment

The environment and the source of the fire are important. In some environments, it is very difficult to detect fire using computer vision due to light exposure, and in some environments it is impossible to install cameras, such as SVM to improve the recognition rate. Overall, the improvements made to the YOLO algorithm have resulted in higher object recognition accuracy and shorter processing times. However, there is still more research and development work to be done in this area to further improve the performance of object recognition models.

A survey of the literature on deep learning (Nguyen et al.)-based wildfire detection using all CNN models was done by the authors in (Bahhar et al.). The Light-YOLOv4 reportedly has a mAP@0.5

of 85.64% and a performance of 71 FPS 1 for jobs involving flame and smoke detection. As a result, YOLO detects fires pretty effectively, especially with Light-YOLOv4's enhancements. To increase the precision of fire detection systems, the YOLO architecture has also been integrated with other machine learning methods, such as ensemble CNNs. The coordinated attention mechanism (CA) was employed in (J. Lin, H. Lin, and Wang) to enhance and broaden the model's focus, particularly on forest fires.

Many publications deal with forest fire detection using YOLO as a detection framework." (Bahhar et al.) (R. Xu et al.) (Xue, H. Lin, and Wang) (Al-Smadi et al.) (Ghali and Akhloufi) using a drone camera. The environment, whether indoor or outdoor, is important before the model is created. To train the model for a particular environment, certain datasets are needed, such as in (Wu et al.), which is about fire detection in ships, but the authors had difficulty finding datasets to train the model. To overcome this obstacle, they used a technique called "**Transfer Learning Method**" to train a model with a different environment for fire detection and half train the model with the actual environment (ship). This produced a promising result. The transfer learning process is faster and more accurate.

(Ghali and Akhloufi)The author created a table (Table 1) listing other publications that preferred to start with a pre-trained model already capable of detecting fire and smoke, such as VGG-x, AlexNet, GoogleNet, ImageNet, and MobileNet, based on transfer learning. To make the model even more accurate, they added an attention model to it. (Wu et al.) The transfer learning method with an attention model was used to detect the fire accurately.

2. YOLO Usages and Comparisons on Fire Detection

Numerous articles on fire detection utilizing YOLO methods and other detection methods have been published recently (2020-2023). In terms of accuracy and speed of fire detection, several papers have demonstrated encouraging results. To increase the robustness and dependability of these methods in practical settings, more study and development are necessary. The SSD (Single Shot Multibox Detector) was proven to be superior in terms of efficacy, detection accuracy, and early fire detection

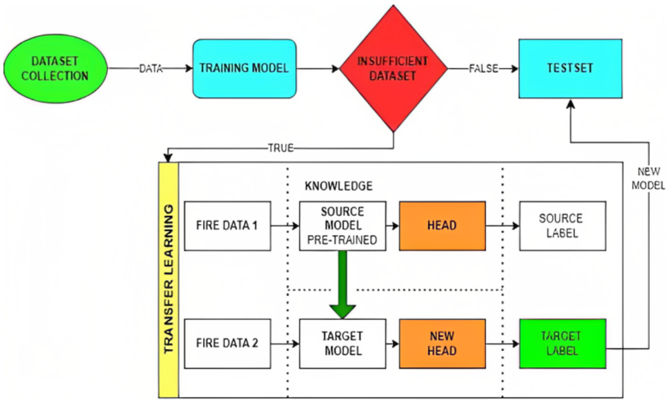

FIGURE 1. Transfer learning aids in handling the problem of the model being trained with insufficient datasets. Transfer learning basically means reusing a trained neural.

capability in (R. Xu et al.). However, a novel ensemble learning approach presented for wildfire detection, (Al-Smadi et al.) publishing, combines Yolov5 and EfficientDet (a type of object detection model that uses various optimization strategies) to increase the detection rate of YOLO. This study examines various YOLO detection models using a novel framework that lessens their sensitivity to earlier approaches. The results indicate that employing data augmentation approaches, detection accuracy has increased. YOLOv7 performs better than YOLOv3-v5 with a **95%** mAP accuracy.

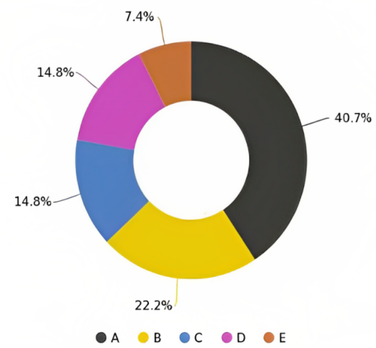

FIGURE 2. Chart of YOLO usage and comparisons done by publications between the years [2020–2023] of survey.

A - Compared YOLO Frameworks with Improved YOLO frameworks. - 40.7%

B - Compared YOLO Frameworks with attention modules - 22.2%

C - Compared YOLO Frameworks with and without data augmentation techniques. - 14.8%

D - Compared YOLO Frameworks models with light-weight models (Tiny-YOLO). - 14.8%

E - Others - 7.4%

In Figure 2, 40.7% of the papers compared the most recent or enhanced YOLO framework with the existing (traditional) YOLO framework. The comparison of the existing YOLO framework with attention techniques like the widely utilized soft-attention-based mechanisms in computer vision was the topic of 22.2% of the publications. To enhance the training set for the model, data augmentation approaches were utilized in 14.8% of the articles. Another 14.8% enhanced the performance of the model using lightweight YOLO models like Tiny-Yolo. In addition to review papers, another 7.4% of the publications concentrated on tweaking the YOLO model's hyper parameters for improved outcomes. Overall, the analysis demonstrates that scientists are consistently investigating new strategies to enhance YOLO's performance for object recognition tasks. To overcome some of the restrictions and difficulties linked to this paradigm, more study is necessary.

(Moumgiakmas, Samatas, and Papakostas)offered an overview of the literature on UAVs with computer vision for fire detection. Faster R-CNN, according to the author, provides superior results with accuracy of up to 90%. Using Metric - Precision, YOLO v3 produces fantastic outcomes. When employing YOLO up to 50%, certain works produce subpar outcomes. In order to enhance performance, local binary patterns, Support Vector Machines (SVM) and Artificial Neural Networks (ANN) were used. Some of the works used ResNet50, Net F1, ERNet, AIDER, and ERNet. The final scores for Emergency Net F1-score were 95.7%, ResNet50 was 96.4%, and AIDER was 96%. According to the year of publishing (2021), neither YOLO v4 nor v5 findings were acquired.

2.1. Attention mechanisms used to detect smoke,fire

The object detection attention mechanism in computer vision gives more weight to critical areas while giving less weight to irrelevant parts. Over the years, numerous publications have enhanced YOLO's functionality and removed constraints by utilizing the Attention Mechanism. .

2.1.1. Models with attention mechanism and Visualization techniques

Publications have used different types of attention mechanisms to overcome certain types of constraints and increase performance and recognition rates.

TABLE 1. Attention mechanism and recognition rate - the experiments and records conducted by the authors (accuracy, mAP@0.5, etc.)

Methods		Detection Rate
Light-BiFPN-YOLOv5n(Se)+ SepViT (H. Xu, Li, and Zhong)	:	mAP@0.5 - 70.9%
I-YOLOv4-tiny+ SE(Squeeze-and-Excitation) (Wu et al.)	:	mAP@0.5 - 0.906
TCA-YOLO (CA(Channel Attention)) (J. Lin, H. Lin, and Wang)	:	mAP@0.5 - 84.56
Grad-CAM (Ding et al.)	:	accuracy - 95.40%
STSAN(SpatioTemporal Self-Attention) (Yang et al.)	:	accuracy-96.5%
STCNNsmoke (Jin et al.)	:	F1' Score - 85.75%

There is NO one "**best**" attention mechanism for fire detection, as it depends on the specific environment and data set used for smoke and fire detection. Various attention mechanisms have been proposed and used in publications to address specific limitations.

In (H. Xu, Li, and Zhong),The authors utilized a global attention system and Light-BiFPN, which increases the link between space and channels by selectively enhancing informative characteristics while suppressing less helpful ones using SE blocks.This lessens the information that a fire loses regarding the flames & smoke, strengthen global dimension features, and improve fire detection accuracy.

GA = softmax(Wg * relu(Wx * X))

where X = input feature map, Wx and Wg are matrices with learnable weights, relu denotes the rectified linear unit activation function, and softmax computes a channel-wise attention vector used to compute a weighted sum of X along the channel dimension to obtain a context vector. (Wu et al.) stated that, SE attention mechanism is suggested for use in ship fire detection, although there doesn't appear to be any pertinent research on it. The presence of a fire at a certain location may be determined using the attention mechanism SE. The squeeze operation's input and result equations are written as tr(WX) X', wherein X is the input value, W is a weighted matrix, and tr is a matrix's trace. The final result of the excitation operation is produced by multiplying X' by an activation function with a sigmoid. The formula for the excitation operation can be expressed as F(X') σ(W_2g(W_1X')), where σ is the sigmoid activation function, W_1 and W_2 are weight matrices, and g is a ReLU activation function. (J. Lin, H. Lin, and Wang) Coordinate Attention (CA) mechanism for improving attention to wildfire targets.

CA(x) = softmax(f(x)) * g(x)

f(x) and g(x) are two accessible functions that produce attention mappings on the channel and dimension of space, respectively, where x is an input feature map.The softmax function is applied to normalize the attention maps along the spatial dimension.

(Yang et al.)used the spatio-temporal self-attention mechanism for capturing the most relevant spatial & temporal features of the input data for accurate fire detection and segmentation.

S = softmax(Q * K^T / sqrt(D_k)) * V

Where S will be a self-attention matrix, D_k is dimension of the key matrix, and Q is query, K will be Key, and V is the Value of Matrices, respectively. In (Ding et al.),Integration of YOLO with Grad-CAM was accomplished by modifying the YOLO architecture to incorporate the Grad- CAM visualization technique. The gradient of the resulting class score in relation to these map features is calculated when the YOLO model generates an estimation for an input picture using the feature maps from the final convolutional layer. The portions of the input picture that were crucial to the object's detection decisions are highlighted on a heat map created using this gradient to weight the feature maps.

Other work (Mardani, Vretos, and Daras) (Lu et al.) has used optimized attention mechanisms in the backbone network, a bidirectional feature pyramid network, small target detection layers, and a majority voting mechanism for video frames.

2.1.2. Overview of Attention mechanisms in Fire detection

Basically called (CenterTracker - mostly used in object tracking in videos) and a permutation self-attention mechanism.

Light-BiFPN-YOLOv5n SepViT (H. Xu, Li, and Zhong) has a high mAP@0.5 score based on the accuracy measures mentioned in Table 1, indicating that it works well in accurately detecting fire. TCA-YOLO (CA) (J. Lin, H. Lin, and Wang) and I-YOLOv4-tiny SE (Wu et al.) also have high hit rates. Grad-CAM (Ding et al.), STSAN (Spatio-Temporal Self-Attention) (Yang et al.), and STC-NNsmoke (Jin et al.), (Mardani, Vretos, and Daras), and (Lu et al.) are methods for viewing and comprehending the activation maps of a trained fire detection model rather than object identification models. These methods can be used to learn more about how a model produces predictions and which elements of an image are used to do so. However, the models showed promise in terms of fire detection.

TABLE 2. Top 3 paper publication with good results and strategy.

Paper	Readings	FPS
(Al-Smadi et al.)	mAP accuracy = 96.8%	FPS = 122
(Wu et al.)	mAP = 0.906	FPS = 51
(J. Lin, H. Lin, and Wang)	TPR = 98.03 FNR = 1.97	FPS = 53.7

3. Top 3 Papers with good proposal Models

3.1. Paper - (Al-Smadi et al.)

Performance Score = 96.8%

Overview -

A new approach that the authors suggested reduces the sensitivity of several YOLO detection techniques. It contrasts uncommon YOLO models like YOLOv3, YOLOv5, and YOLOv7 with predecessor models like Fast & Faster R-CNN in terms of detection, public display and speed. On the multi-level dataset for detective work in wild smoke, the simulate surpassed the gold-standard detection approach by a mAP accuracy - 96.8% at an 0.5 IoU using YOLOv5x. Study's findings demonstrate a significant advancement in the use of various data-augmentation strategies for truth identification. When applied to fume datasets from wildfires, Numerous studies show that the proposed method performs copestically in challenging environmental circumstances and achieves superior outcomes than the most sophisticated object-detection algorithms.

3.1.1. Dataset

The authors employed a collection of data that is online accessible and was taken from the Kaggle archives. It contains 737 unique photographs with different locations and detecting zones like close - medium - distance. In order to get the total number of images to 1723, In the data-augmentation procedure, the number of grooming elements from the new photographs were multiplied by three in an updated version of the data set. They then reduced the size of the photographs to 640*640 in order to boost the rate of detection.

3.1.2. Paper's Method

The proposed model for detecting forest fire smoke involves the following steps:

1.Collecting Dataset to train the model

2.Using some Data Augmentation techniques

3.Comparing the trained model with other YOLO models

4.Comparing the trained model with other Non-YOLO models

5.Applying some optimizer techniques to improve the detection rate

6.Evaluation and Testing

The purpose of this work is to establish the best detection algorithms(Model) for detecting fires in the least amount of time, with the capacity to detect from multiple detection zones, including close - medium - far.

3.1.3. Competitors (Models

YOLO Models and Other CNN Models

Using data augmentation methods to lessen sensitivity and the stochastic gradient descent optimizer to boost performance. The findings indicate that, of all models tested in this study, YOLOv5x model attained the highest detection accuracy. The suggested model seeks to precisely and effectively identify smoke from forest fires in various detection regions, including close, medium, and distant.

3.2. Paper - (Wu et al.)

Performance Score = 90.6%

Overview -

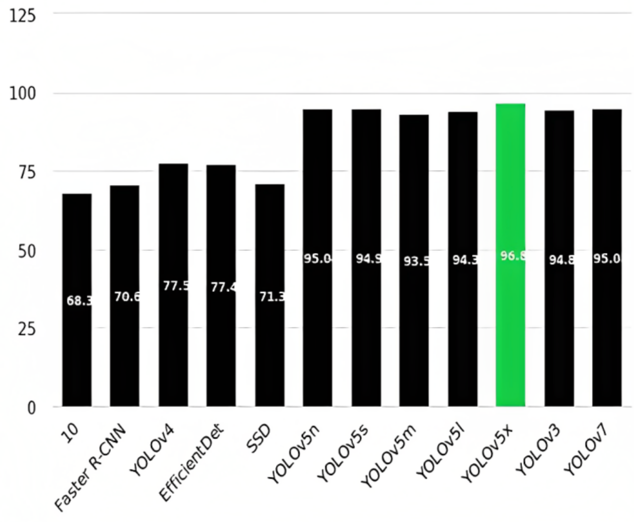

Chart 1: contrasting the effectiveness and speed of detection between current YOLO models like YOLOv3, YOLOv5, and YOLOv7 with earlier models like Fast & Faster R-CNN. evaluating the detection precision of the other YOLO models.

This paper presents a lightweight object recognition system based on the improved YOLOv4-tiny algorithm for accurate and efficient fire detection in ships. While the proposed method employs the SE attention mechanism to consider Cross Channel feature fusion, To strengthen the detection window and include deep semantic information a multi-level detection strategy is employed. To speed up area coverage and detection, the small ship fire dataset is augmented with computer vision and transfer learning. The simulation results stated, the proposed model outperforms the baseline techniques in terms of accuracy and effectiveness in ship fire detection.

3.2.1. Dataset

In this paper, the web crawler has been used to collect and eliminate blurry photographs from the ship fire detection dataset. The gathered images were scaled to a size of 416*416 and normalized before manual labeling. To increase the self-generated dataset to 2160 images and randomly divide them into - training, validation, test sets. The photos were inverted, the aspect ratio was skewed, and the color scale was altered. The convolutional neural network method in detecting ship fires has drawbacks, including the need to train a large amount of training data, and pricey hardware platforms. As a starting point, two land fire datasets are employed; poor quality images are then omitted, and a new dataset with numerous flames underscoring the information features is produced. because the ship fire dataset is readily available.

3.2.2. Paper's Method

1.Collection the Dataset to train model for specific environment

2.Image manipulation technique was used to improve and increase the dataset

3.The Multi-Scale Detection strategy was applied to detect the flame with sizes

4.Getting posterior frame parameters of other sizes and the labeled data samples were clustered using K-Means algorithm.

5.In order to concentrate on important details and ignoring unwanted data, the SE attention mechanism was applied in their method.

6.An enhanced YOLOv4-tiny method was used to create a compact convolutional neural network model for fire detection in ships.

7.Comparing the trained model with other detection models and testing

3.2.3. Competitors

YOLOv4-tiny vs Improved YoloV4-tiny.

A layered detection strategy was used by the authors to broaden the detection dimensions after they developed a high-quality data collection of ship fires. Because of its high precision and quick detection speed, the authors believe that their suggested model, Improved YOLOv4-tiny + SE, has a lot of possibilities for usage in the shipping sector.

3.3. Paper - (J. Lin, H. Lin, and Wang)

Performance Score = 89.56%

Overview -

The authors suggest using YOLOv5 as the foundation of the TCA-YOLO (enhanced version), a forest fire detection model. By combining the feature extraction network and the Transformer encoder, you may improve the collection of global data on wildfire targets, which has excellent global modeling capabilities and a self-attention mechanism.

3.3.1. Dataset - (Image / Video)

The dataset used in this study consists of 3000 photos of different forest fire situations taken by drones and video surveillance equipment in forested areas, as well as publicly accessible forest fire datasets. A wildfire detection model was trained using 1000 manually labeled and converted to YOLO data format photos, of which 700 were randomly divided into 300 for testing and the remaining 700 used to train models. 2000 more unlabeled pictures of forest fires were added to the training set in order to adopt a semi-supervised learning technique.

3.3.2. Method

1.Online mosaic enhancement is used for preprocessing to improve the overall quality of the input images and decrease false alarms.

2.Feature Extraction: The preprocessed images are utilized to extract features using a YOLOv5-based architecture

3.Adaptively Spatial Feature Fusion - The ASFF module was used to filter away useless information from other layers in order to properly fuse features and reduce the influence of varied backdrops on detection in the forest area.

4.Coordinate Attention Mechanism: CA mechanism was used to improve the model's focus towards forest fire targets by adjusting the weight of the target.

5.Detection: Last feature map is used to recognise objects, particularly targets for forest fires

6.Semi-Supervised Learning: During training, Semi-supervised learning reduces the level of manual labeling necessary by using a little quantity of labeled data and a large number of unlabeled data.

7.Evaluation: A variety of measures, including precision, recall, precision, accuracy, and F1 score, are employed to evaluate how well the proposed approach works.

The results of the experiments show that the suggested technique outperforms existing cutting-edge technology when it comes to accuracy and efficiency. The suggested model's overall goal is to offer an effective solution for real-time fire detection in Forest.

According to the authors, the coordinated attention (CA) mechanism is incorporated to enhance the model's emphasis on its objectives. Finally, a large portion of the manual labeling work is saved via semi-supervised learning. According to experimental findings, TCA-YOLO's average accuracy is 5.3% greater than YOLOv5's average accuracy. In many instances, TCA-YOLO also performed better at identifying wildfire targets. The capacity of TCA-YOLO to extract the global data targets was substantially improved, and it was able to locate forest fire targets with increased precision. 53.7% of FPS

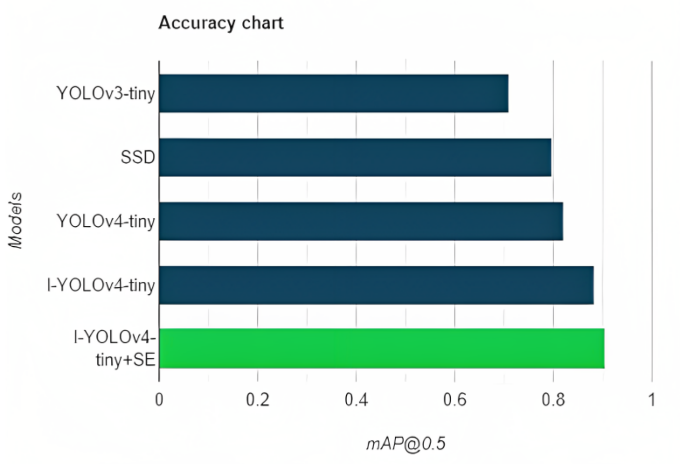

Chart 2: **Comparison (accuracy) chart of this paper**

was attained,demonstrating that the detection speed meets the real-time forest fire detection's requirements. An updated model, TCA-YOLO, was proposed using YOLOv5.

3.3.3. Competitors

YOLOv5 and TCA-YOLO (Yolo with attention features)

TABLE 3. **Performance Table of the proposed model.**

Strategies and Model	mAP@0.5
YOLOv5	79.26
YOLOv5 + Transformer	81.56
YOLOv5 + Transformer + CA	82.78
YOLOv5+Transformer+CA+ASFF(TCA - YOLO)	84.56

4. Discussion

Using the detection score, these three methods are chosen as the top three fire detection methods. For the score, the fire detection rate and FPS (performance) are taken into account. The main factors used to determine the score were the datasets used, experiments performed in real-time, tools used, and information provided. Numerous data augmentations and tunings have been employed by (Al-Smadi et al.).The division of responsibility for publishing (Al-Smadi et al.) is as follows:From Google and Kaggle libraries, the authors gathered the equivalent of 6,000 images of forest fires and smoke. The development of techniques like rotation and flipping helped to lessen sensitivity to image orientation. The performance and accuracy of different YOLO models were compared by the authors. To enhance performance and reduce detection times, the authors adopted a stochastic gradient descent optimizer.The authors examined the effectiveness of the proposed model using a number of different evaluation measures, including mean average precision (mAP). (J. Lin, H. Lin, and Wang) have effectively fused features to reduce the interference of complicated backdrops before detection by using attention and other techniques like The ASFF module filters out unwanted information while detecting fire. The split for publishing (J. Lin, H. Lin, and Wang) is shown here.

From Google and Kaggle libraries, the authors gathered images of forest fires and smoke. The development of techniques like rotation and flipping helped to lessen sensitivity to image orientation. To enhance performance and reduce detection times, the authors adopted a stochastic gradient descent optimizer. The authors assessed the effectiveness of the proposed model using a range of metrics, including the mean average precision. (Wu et al.) Creating a high-quality dataset manually due to the dataset's limited availability. To increase the range of detectable dimensions the multi-scale detection technique was used by authors. enhanced SE attention mechanism and YOLOv4-tiny algorithm for ship fire detection. the proposed method's evaluation on embedded devices - Comparative analysis of alternative cutting-edge techniques for ship fire detection.

4.1. Common strategies Table of the publication

TABLE 4. Approaches that the papers utilized. These are the standard inputs that all fire detection tools use. using these methods to evaluate the top 3 papers.

Parameters (strategies)	(Al Sm et al.)	(Wu et al.)	Lin, Ji, Haifeng
Data Collection	Yes	Yes	Yes
Data augmentation	Yes	Yes	Yes
Detection model selection	Yes	Yes	Yes
Hyperparameter tuning	Yes	Unknown	Yes
Pre-trained model	Yes	Yes	No
Attention Mechanism	Yes	Yes	Yes
Transformer	Yes	No	Yes
Simulation device setup	Yes	Unknown	Unknown
Real-time experiment	No	No	No

4.2. Pretrained Models

The YOLOv5 pre-trained model for object detection was employed by the authors in (Al-Smadi et al.).For picture classification, they also employed a pre-trained model called EfficientNet. Using transfer learning, the pre-trained models were adjusted using the amassed dataset of photographs of forest fire and smoke. (Wu et al.) The backbone network for the authors' suggested model was a pre-trained model. They specifically employed the YOLOv4-tiny model that had already been trained on the COCO dataset as the backbone network and then enhanced it by including SE attention mechanisms and ship-specific features. In order to tailor the pre-trained model to the specific goal of ship fire detection, the authors also made adjustments to it using their built-in ship fire dataset. (J. Lin, H. Lin, and Wang) The suggested solution bases its identification algorithm on a YOLOv5 model that has already been trained. Using the suggested semi-supervised learning method, the pre-trained YOLOv5 model is adjusted on a dataset of photos of forest fires. Along with the tuned YOLOv5 model, the adaptively spatial feature fusion (ASFF) module and coordinate attention mechanism are also learned throughout the training procedure. As a result, a pre-trained model is utilized as a starting point and is then further trained and improved on a particular dataset for detecting forest fires.

5. Conclusion

As a vital tool for early warning and fire prevention, the deep learning algorithms of YOLO enable real-time and accurate fire and smoke detection. YOLO's capacity to detect many items at once improves monitoring capabilities, making it especially useful for keeping an eye on expansive areas like woods or industrial sites and lowering the chance of devastating fires. The review also stresses how crucial it is to identify the best detection models with the capacity to detect from diverse detection areas in order to spot fires in the least amount of time.Although the previous three years (2020-2023) are the main emphasis of this research, it offers a thorough summary of the state of YOLO-based fire detection systems today, including a comparison of published studies, datasets used, methodology, and performance evaluation. Overall, the review's conclusions show that YOLO has a promising future in the field of smoke and fire detection, opening the door for more development and developments in fire protection technology. The most effective fire detection technique may vary depending on the application, resources available, environment, and desired level of accuracy. As a result, it is advised to thoroughly assess and contrast various fire detection technologies based on their effectiveness, performance, and suitability for the particular application.

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