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Smoke and Fire Detection using Deep Learning: A Review

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Abstract: *The fire and smoke monitoring systems are useful in numerous industries like military, Social Security and economical. The recent methods for fire and smoke detection are used only motion and colour characteristics thus many wrong alarms are happening and this is often decrease the performance of the systems. During this study, we will observe the way we are able to divide the smoke columns with object detection and a deep learning-based approach and convolutional neural network (CNN) model for extracting smoke features and smoke detection. The colour, motion and disorder are useful characteristics in fire and smoke detection algorithm. Smoke of fireplace will blur the entire or a part of the photographs. Thus by processing of the frames, different objects will detect. Because of evaluate the features of objects, the goal objects (fire and smoke) will be defined easily. The results of the study have broad application prospects within the important military, social insurance, forest-fire alarm, commercial applications, and so on. preprocessing, feature extraction, and fire detection. Among, feature extraction is that the core part in algorithms. Traditional algorithm depends on the manual selection of fireplace whereas algorithms of deep learning, Convolutional Neural Networks (CNNs) like GAN, SS-GAN, DCGAN, DCNN, AlexNet, VGG, Bi-LSTM, Inception, ResNet, RetinaNet Faster R-CNN can automatically learn and extract complex image features effectively. These processes has many advantages like early fire detection, high accuracy, flexible system installation, and the capability to effectively detect fires in large spaces and complicated building structures.*

Keywords: Smoke detection, Fire detection, Wildfires, Deep learning, Convolutional neural network (CNN)

I. INTRODUCTION

In the economic development, the hearth control has become great challenge within the constructions due to the increasing scale and complexity. Therefore, we'd like fire detection and alarm with high sensitivity and accuracy to cut back fire losses. Traditional fire detection technologies, like smoke and warmth detectors, don't seem to be suitable for giant spaces, complex buildings, or spaces with many disturbances. The restrictions of above detection technologies, missed detections, false alarms, detection delays and other problems often occur, making it even tougher to attain early fire warnings. Recently, image fire detection has become a trend within the research part. In this process the image's data from a camera is collected by algorithms to work out the presence of a fireplace in images. Therefore, the detection algorithms are the main part of this technology, it directly determining the performance of the image fire detector. There are three main stages within the process of fire detection algorithms, including image

II. LITERATURE SURVEY

1. Yin, H., Wei, Y., Liu, H., Liu, S., Liu, C., & Gao, Y. (2020). Deep convolutional generative adversarial network and convolutional neural network for smoke detection. Complexity, 2020. This paper mainly includes the following contributions:

1. The vibe algorithm
2. DCGAN
3. CNN

In this article, author compares traditional algorithms and the deep learning algorithms like GAN, SS-GAN, DCGAN. The selected new algorithms give more accuracy in both the training and testing case studies. Thus the author concludes that these experimental results has better accuracy and reduces the false alarm rate for various forms of smoke appearances.

2. Gaur, A., Singh, A., Kumar, A., Kumar, A., & Kapoor, K. (2020). Video flame and smoke based fire detection algorithms: A literature review. Fire technology, 56(5), 1943-1980 In this paper, the author proposed handcraft feature with or without classifiers and deep learning approaches. The author gives a clear idea by how handcraft rules, classifiers based fire flames and smoke detection are used and by also using deep learning. In deep learning approach, CNN is used for fire detection and smoke detection in images and videos. Some initial works used DCNN alone to detect flames and smoke. It also been noticed that, there is a drawback of using CNN's for fire detection is that these have high memory and computational needs. Present it can detect in some of the locations using these approaches but in Future it may give better detection results in other locations like tunnels, parking places and in forest environments.

3. Zheng, X., Chen, F., Lou, L., Cheng, P., & Huang, Y. (2022). Real-Time Detection of Full-Scale Forest Fire Smoke Based on Deep Convolution Neural Network. Remote Sensing, 14(3), 5361. This paper evaluates the effectiveness of using deep convolution neural network to detect fire smoke in real time. Based on various CNN model like AlexNet, VGG, Inception, ResNet etc., the smoke and flame detection algorithms were also investigated during this paper. To investigate which deep CNN algorithm can perform the simplest for early fire detection, this paper implements and compares four deep CNN algorithms for fire detection in real time. The average measurement accuracy and detection speed of 4 investigated deep CNN algorithms compares the measurements accuracy and therefore the mean, additionally to the detection time of 4 algorithms. This paper concludes that everyone the four investigated algorithms achieved acceptable average accuracy.

4. F.Guede-Fernández, F., Martins, L., de Almeida, R. V., Gamboa, H., & Vieira, P. (2021). A deep learning based object identification system for forest fire detection. Fire, 4(4), 75. In this article comparison between the use of RetinaNet and Faster R-CNN was performed. The RetinaNet and Faster R-CNN models were trained for smoke classification with specific parameters and datasets. These models are trained with high, mid and low smoke level images. The time taken to detect the fire from start of the incident was 5.5 min on average for the same 8 sequences.

5. Fernandes, A. M., Utkin, A. B., & Chaves, P. (2022). Automatic Early Detection of Wildfire Smoke With Visible Light Cameras Using Deep Learning and Visual Explanation. IEEE Access, 10, 12814-12828. Author states that in this paper Support Vector Machines (SVM), Hidden Markov Models (HMM), Kalman filters, etc., frequently used to analyze features such as color, wavelets, texture, or motion of smoke. The present article indicates that when no mosaic output issused but rectification is employed to assure that neural networks are focusing on the desired features, the true positive percentages and AUROC are smaller than in the case without rectification.

III. COMPARISION TABLE

Sl. No.	PAPER NAME	YEAR	DESCRIPTION	LIMITATIONS	ADVANTAGES	PERFORMANCE METRICES
1	Deep Convolutional Generative Adversarial Network and Convolutional	2020	To overcome these issues, a Graph-based Feature Extraction and Hybrid	Wind direction, wind speed, light, and other factors in the actual environment will have a great impact on the smoke.	Vibe algorithm has good applications in moving object detection. We can make use of the background for	The proposed approach is proved with its increased recognition rate.

	Neural Network for Smoke Detection		Classification Approach (GFE-HCA) is proposed for recognizing the facial expressions		static feature extraction and classification	
2	Video Flame and Smoke Based Fire Detection Algorithms: A Literature Review	2020	These are mainly based on handcraft features with or without classifiers and deep learning approaches	The behavior of flame and smoke also dependson their distance from the camera, background, day or night time and many such factors.	Some of them are good cues of fire but may require computationallyrigorous algorithms while some are opposite.	The Faster R-CNN with Inception ResNetV2 is best in terms of accuracy but it is slowest
3	Real-Time Detection of Full-Scale Forest Fire Smoke Based on Deep Convolution Neural Network	2022	Machine vision and image processing Technology is widely used for detecting forest fire smoke.	The deep learning algorithms also have their limitations. Most of the existing deep learning algorithms consider fire detection as a classification problem and ignore the region identification process such that the entire image was classified into one category	The deep CNN algorithm can automatically extract complex image fire features for Fire detection in different scenes.	The Efficient Det algorithm achieves an average detection accuracy of 95.7%, which is the best real-time forest fire smoke detection among the evaluated algorithms.
4	A Deep Learning Based Object Identification System for Forest Fire Detection	2021	This paper uses deep learning approach.	It can't differentiate night-time images. It may not distinguish clouds and smoke. The HPWREN dataset have a clear view of the horizon without obstructions.	These models are trained with hrz, mid and low smoke classes.	The time elapsed from the start of the fire until it is first detected was 5.5 min on average for the same 8 sequences.
5	Automatic Early Detection of Wildfire Smoke With Visible Light Cameras Using Deep Learning and Visual Explanation	2022	Algorithms tested were residual neural networks (ResNet) and EfficientNet	The mosaic output does notalways lead to better results.	The best overall neural network created is the EfficientNet-B0 configuration, which possesses the smallest number of trainable weights among all the neural networks tested.	The AUROC value of 0.949, obtained with the test set, corresponds to true and false positive percentages of 85.3% and 3.1%, respectively.
6	A Deep Normalization	2017	novel deep normalization	Unlike algorithms based on handcrafted	It can automatically extract features for	Results show that our method

	and Convolutional Neural Network for Image Smoke Detection		and convolutional neural network (DNCNN) with 14 layers to implement automatic feature extraction and classification.	features, our DNCNN can automatically extract features forsmoke detection.	smoke detection. It also achieves high detection rates and low false alarm rates at the same time	achieved very low false alarm rates below 0.60% with detection rates above 96.37% on our smoke data sets.
7	An Attention Enhanced Bidirectional LSTM for Early Forest Fire Smoke Recognition	2019	In this paper, we propose a novel Attention Enhanced Bidirectional Long Short-Term Memory Network (ABi-LSTM) for video based forest fire smokerecognition.	To ease the limitations of smoke image samples, an end-to-end trainable framework based on fast detector SSD and MSCNN for smoke detection is proposed, which can optimize the model from synthetic andreal smoke samples.	the proposed ABi-LSTM framework obtains higher accuracy in early forest fire smoke recognition compared with other methods.	This method achieved a high accuracy of 97.8%
8	Dual Deep Learning Model for Image Based Smoke Detection	2019	This paper uses Deep Convolutional Neural Networks	It does not give 100% accuracy.	This algorithm is applicable in any conditions like wild-smoke, distance or nearby smoke, cloudy, fog or mist etc.	Accuracy for CNN is 92.3% and for SVM is 98.29%
9	KutralNet: A Portable Deep Learning Model for Fire Recognition	2020	One of the new approaches to the problem is the use of images to perform the detection.	It does not gain 100% accuracy in this paper.	Our proposed model KutralNet obtains better accuracy and AUROC index than previously deep learning models for fire recognition, with just a few layers and with a considerable reduction in computational cost	One of our models presents 71% fewer parameters than FireNet, while still presenting competitive accuracy and AUROC performance.
10	A Real-time Fire Segmentation Method Based on A Deep Learning Approach	2022	This paper uses the lightweight network to build a new deep convolution neural network.	This algorithm takes long time for evaluation.	This method is an encoder-decoder structure network. This method is an improved version of deeplabv3+	This method gives an accuracy of 92.46% to 86.98%.
11	FIgLib&Smok	2022	This paper uses	Neither of these	one limitation is	This achieved an

	eyNet: Dataset and Deep Learning Model for Real-Time Wildland Fire Smoke Detection		deep learning approaches for wildlife smoke detection.	methods improved model performance.	that this ratio is not representative of real-world scenarios in which positive examples of visible smoke are much more rare than negative	average accuracy of 78.5%.
12	Convolutional neural network based early fire detection	2020	In this paper, we proposed a fire detection method which is based on powerful machine learning and deep learning algorithms	WSN based strategiesrequire an extensive amount of smoke, heat or gas for detection.	The purpose of Adaboost-LBP model is to find emergencies fromthe image and to generate ROI of that detected object.	The accuracy of ourproposed model is more than 99%. It can be more accurate after more training.
13	Low-Complexity High-Performance Deep Learning Model for Real-Time Low-Cost Embedded Fire Detection Systems	2020	Most deep learning systems outperform the hand-crafted algorithms for fire detection, particularly due to the enormous potential offered by Convolutional Neural Network and its variants.	We dint get the desired accuracy.	Our method outputs the best performance in terms of accuracy, precision, false positives, and F-measure metrics. The model also gives a good value of recall while keeping the false negatives to sufficiently low value.	The accuaracy is 0.94%.
14	False Positive Decremented Research for Fire and Smoke Detection in Surveillance Camera using Spatial and Temporal Features Based on Deep Learning	2019	we introduce a novel smoke detection algorithm that reduces falsepositive detection using spatial and temporal features based on deep learning from factory installedsurveillance cameras.	a deep learning method using the shape of an object frequentlygenerate false positives, where general object is detected as the fire or smoke.	The frame similarity using SSIM and MSE. Second, we adapted the Faster R-CNN algorithm to find smoke and fire candidate region for the detected frame	-------------------

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15	Fire Detection Method in Smart City Environments Using a Deep-Learning-Based Approach	2021	Weexamined the originalYOLOv4 approach to determine the accuracy of predictions of candidate fireregions. However, the anticipated results were not observed after several experiments involving thisapproach to detect fire accidents.	This cannot be done in real time.	CNN were explored using large databases to make accurate predictions and control overfitting issues.	The testing accuracy is 96.3%.

IV. METHODOLOGY

4.1 GAN

Generative adversarial network (GAN) is an exciting recent innovation in deep learning. GAN is generative model which means they can create new data instances that resemble your training data.

In GANs, there's a generator and a discriminator. The Generator generates fake samples of information (like image, audio, etc.) and tries to fool the Discriminator. On the other hand, the Discriminator tries to tell apart between the important and faux samples. The discriminator filters through the knowledge and returns a probability between 0 and 1. 1 correlates with real data and 0 correlates with fake data. These values are then manually checked for achievement and repeated until the required outcome is reached. The Generator and also the Discriminator are both Neural Networks and that they both run in competition with one another within the training phase.

4.2 Types of GAN

- Vanilla GAN
- Conditional GAN (CGAN)
- Deep Convolutional GAN (DCGAN)
- Laplacian Pyramid GAN (LAPGAN)
- Super Resolution GAN (SRGAN)

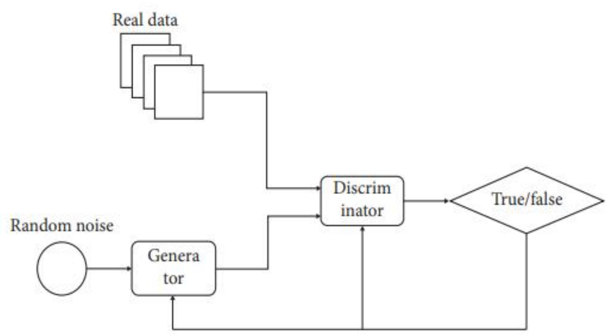

Fig1: GAN model composition. The generator model generates the images and differentiates whether the sample is real or not.

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A. DCNN

Deep convolutional neural networks (DCNN) are the sort most typically won't to identify patterns in images and video. DCNN have evolved from traditional artificial neural networks, employing a 3-D neural pattern. Deep convolutional neural networks are mainly focused on applications like object detection, image classification, and recommendation systems. Convolutional networks were inspired by biological processes there in the connectivity pattern between neurons resembles the organization of the animal cortical region. Types of Deep Conventional Neural Networks:

- R-CNN
- Fast RCNN
- GoogleNet
- VGGNet
- ResNet
- DNCNN

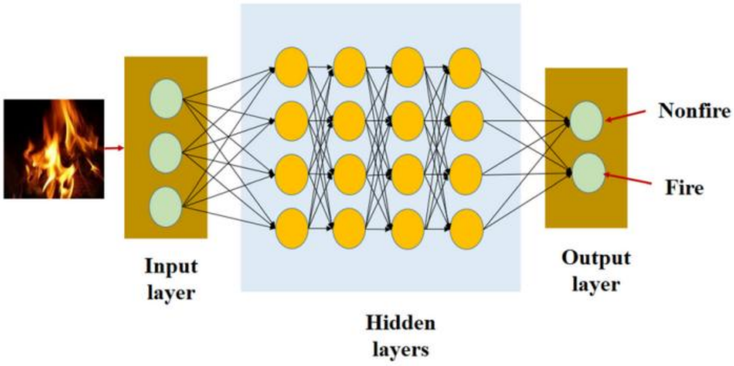

Fig2: A DCNN model for smoke and fire detection.

B. Bi-LSTM

Long Short Term Memory (LSTM) is a type of reasonably recurrent neural network. In RNN output from the last step is fed as input within the current step. It tackled the matter of long-term dependencies of RNN within which the RNN cannot predict the word stored within the remembering but can give more accurate predictions from the recent information. As the gap length increases, efficient performance of RNN decreases. LSTM can by default retain the knowledge for an extended period of your time. It's used for processing, predicting, and classifying on the premise of time-series data. A common LSTM unit is composition of

- Cell
- Input gate
- Output gate
- Forgot gate

Bidirectional long-short term memory (bi-lstm) is that the process of creating any neural network which have the sequence information in both directions backwards or forward. In bidirectional, our input flows in two directions making a bi-lstm, this is the difference in the regular LSTM.

This structure allows the networks to own both backward and forward information about the sequence at each time step.

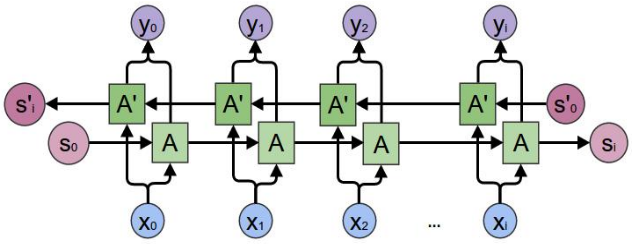

Fig 3: A single layer bidirectional LSTM. We feed spatial features in both forward and backward which allows our model learns both the past and future context information context information from both left and right side over time.

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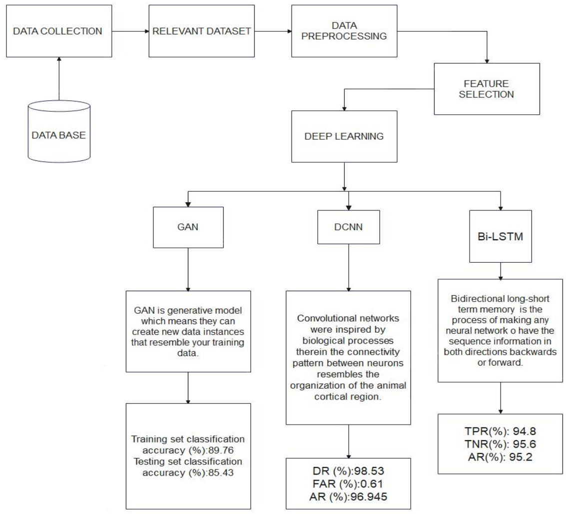

Fig4: Smoke and fire detection techniques classification chart.

V. RESULT AND DISCUSSION

5.1 Methodology-1

In this paper proposes a generative adversarial network and convolutional neural network for smoke and fire detection. By using these algorithms, the model has obtained higher accuracy rates than traditional methods.GAN algorithm doesn't have DR% and FAR%.The obtain ed AR% for this algorithm is 85.43%.

5.2 Methodology-2

In this paper, the author proposed DCNN algorithms for smoke and fire detection. These algorithms performed right strategy for combination of new and original training samples. The DCNN algorithms used and accuracy given by them are as follows:

Table 1: The DCNN algorithms used and accuracy given by them are as follows:

ALGORITHMS	DR%	AR%	FAR%
DNCNN	96.37	98.19	0.60
AlexNet	93.29	97.18	0.26
VGG16	96.19	97.48	0.60

5.3 Methodology-3

In this paper, the author used d bidirectional LSTM. The proposed ABi-LSTM has been inspired by the attention mechanism in neural machine translation, which can adaptively focus on discriminative frames. Bi-LSTM framework obtains higher accuracy in early forest fire smoke recognition compared with other methods. These algorithms give the 97.8% accuracy rate, 97.5% detection rate.

VI. PERFORMANCE METRICS AND VALUATION

DR, FAR, AR represents detection rate, false alarm rate, and accuracy rate respectively.TPR, TNR represents true positive rate, true negative rate respectively. TP, TN, FP, FN represents True Positive, True Negative, False Positive, False Negative respectively. NN, P, N represents the number of negative samples wrongly detected, the number of negative samples, and the number of positive samples, respectively

$$TPR = (TP) / (TP+FN) \quad (1)$$

$$TNR = (TN) / (TN+FP) \quad (2)$$

$$AR = (TP+TN) / (TP+FN+TN+FP) \quad (3)$$

$$DR = TP / P \quad (4)$$

$$FAR = NN / N \quad (5)$$

$$AR = (TP+TN) / (P+F) \quad (6)$$

From the above formulas,
We can equalize

$$TPR=DR \quad (7)$$

As,

$$P=TP+FN \quad (8)$$

$$N=TN+FP \quad (9)$$

Table 2: Recent algorithms proposed for smoke and fire detection and their accuracies.

ALGORITHMS	DR%	AR%	FAR%
GAN	-	85.43	-
SS-GAN	-	89.24	-
DCGAN	-	93.24	-
DNCNN	96.37	98.19	0.60
AlexNet	93.29	97.18	0.26
VGG16	96.19	97.48	0.60
Bi-LSTM	97.5	97.8	-
Inception	93.2	93.4	-

VI. CONCLUSION

In this paper, several deep learning techniques have been applied to detect the smoke and fire in various samples. These techniques mainly focused on handcraft feature image and video based fire and smoke detection. The static and dynamic characteristics of both fire and smoke are mainly focused. The treatment for smoke and fire also differs because they have different prominent features. The behavior of fire and smoke also depends on their distance from the camera, background, day or night time and many such factors. The deep learning and CNN algorithms provides higher accuracy compared to that of the traditional algorithms and fire alarms. These algorithms not only can detect the fire accidents in public, but also can be helpful in forest regions. Therefore, we consider combining the new optimization algorithms with our network model for better smoke detection performance. We should focus on applying smoke detection to real-life or industrial environments, extending to real-time smoke detection. It is of great significance for the prevention of fire in production and life. From the methods we used above, we obtained the highest accuracy rate by using the DNCNN algorithm.

REFERENCES

[1]. Yin, H., Wei, Y., Liu, H., Liu, S., Liu, C., &Gao, Y. (2020).Deep convolutional generative adversarial network and convolutional neural network for smoke detection. Complexity,2020

[2]. Gaur, A., Singh, A., Kumar, A., Kumar, A., &Kapoor, K. (2020). Video flame and smoke based fire detection algorithms: A literature review. Fire technology, 56(5), 1943-1980

[3]. Zheng, X., Chen, F., Lou, L., Cheng, P., & Huang, Y. (2022).Real-Time Detection of Full-Scale Forest Fire Smoke Based on Deep Convolution Neural Network. Remote Sensing, 14(3), 536

[4]. Guede-Fernández, F., Martins, L., de Almeida, R. V., Gamboa, H., & Vieira, P. (2021). A deep learning based object identification system for forest fire detection. Fire, 4(4), 75

[5]. Fernandes, A. M., Utkin, A. B., & Chaves, P. (2022). Automatic Early Detection of Wildfire Smoke With Visible Light Cameras Using Deep Learning and Visual Explanation. IEEE Access, 10, 12814-12828.

[6]. Yin, Z., Wan, B., Yuan, F., Xia, X., & Shi, J. (2017). A deep normalization and convolutional neural network for image smoke detection. Ieee Access, 5, 18429-18438.

[7]. Cao, Y., Yang, F., Tang, Q., & Lu, X. (2019). An attention enhanced bidirectional LSTM for early forest fire smoke recognition. IEEE Access, 7, 154732-154742.

[8]. Pundir, A. S., & Raman, B. (2019). Dual deep learning model for image based smoke detection. Fire technology, 55(6), 2419-2442

[9]. Ayala, A., Fernandes, B., Cruz, F., Macêdo, D., Oliveira, A. L., &Zanchettin, C. (2020, July).Kutralnet: A portable deep learning model for fire recognition. In 2020 International Joint Conference on Neural Networks (IJCNN) (pp. 1-8).IEEE

[10]. Li, M., Zhang, Y., Mu, L., Xin, J., Yu, Z., Jiao, S., ...&Yingmin, Y. (2022). A Real-time Fire Segmentation Method Based on A Deep Learning Approach. IFAC-PapersOnLine, 55(6), 145-150.

[11]. Dewangan, A., Pande, Y., Braun, H. W., Vernon, F., Perez, I., Altintas, I., ...& Nguyen, M. H. (2022). FIgLib&SmokeyNet: Dataset and Deep Learning Model for Real-Time Wildland Fire Smoke Detection. Remote Sensing, 14(4), 1007

[12]. Saeed, F., Paul, A., Karthigaikumar, P., &Nayyar, A. (2020). Convolutional neural network based early fire detection. *Multimedia Tools and Applications*, *79*(13), 9083-9099.

[13]. Jadon, A., Varshney, A., & Ansari, M. S. (2020).Low-complexity high-performance deep learning model for real-time low-cost embedded fire detection systems. *Procedia Computer Science*, *171*, 418-426.

[14]. Lee, Y., & Shim, J. (2019). False positive decremented research for fire and smoke detection in surveillance camera using spatial and temporal features based on deep learning. *Electronics*, *8*(10), 1167

[15]. Avazov, K., Mukhiddinov, M., Makhmudov, F., & Cho, Y. I. (2021).Fire Detection Method in Smart City Environments Using a Deep-Learning-Based Approach. *Electronics*, *11*(1), 73