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Fire detection using deep learning methods

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ABSTRACT

Fire detection is an important task in the field of safety and emergency prevention. In recent years, deep learning methods have shown high efficiency in solving various computer vision problems, including detecting objects in images. In this paper, monitoring wildfires was considered, which allows you to quickly respond to them and prevent their spread using deep learning methods. For the experiment, images from the satellite and images from the FireWatch sensor were taken as initial data. In this work, the deep learning algorithms you only look once (YOLO), convolutional neural network (CNN), and fast recurrent neural network (FastRNN) were considered, which makes it possible to determine the accuracy of a natural fire. As a result of the experiments, an automated fire recognition algorithm using YOLOv4 deep learning methods was created. It is expected that the results of the study will show that deep learning methods can be successfully applied to detect fire in images. This may lead to the development of automated monitoring systems capable of quickly and reliably detecting fire situations, which will help improve safety and reduce the risk of fires.

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1. INTRODUCTION

Fire detection is an important task for ensuring safety and prompt response to fire incidents. In recent years, deep learning methods have proven to be highly effective in solving computer vision problems, including fire detection. The use of deep learning methods allows you to automate and improve the process of fire detection based on the analysis of visual information. Deep learning methods can be used to monitor wildfires [1]–[3] to quickly detect them and prevent their spread. In modern fire detection systems, deep learning methods are playing an increasingly important role, which allow you to automatically analyze visual data and determine the presence of a fire. Deep learning is a machine learning approach based on the use of deep neural networks capable of processing complex data and extracting high-level features.

Some of the deep learning methods that can be applied to wildfire monitoring. One approach is to classify satellite [4], [5] and FireWatch sensor images for fire and smoke detection. For this, deep neural networks such as convolutional neural networks (CNNs) [6], [7] can be used, which can automatically extract features from images and classify [8]–[10] them as containing fires or not. Another approach is to process radiometric sounding (RS) data, which can be used to detect signs associated with fires, such as temperature and brightness. This data can be processed using deep neural networks such as fast recurrent neural networks (fast R-CNN) [11]–[13], which can process data sequences and extract information about fires. The third approach is to combine data from various sources, such as remote sensing data, satellite data, UAV data, and weather station data, to create an integrated fire monitoring system. Deep neural networks can be used to analyze and classify this data, which can process it in real-time and provide real-time information about fires. In general, deep learning methods can be an effective tool for monitoring wildfires, which will help to quickly detect fires and prevent their spread, which in turn will save forests and other natural resources.

The use of deep learning algorithms for fire recognition has become increasingly popular due to their ability to accurately and efficiently detect fires. Several studies have explored various deep-learning techniques for fire recognition, including you only look once version 4 (YOLOv4), CNN, and fast R-CNN. One study by Wu *et al.* [14] proposed an improved version of YOLOv3 called YOLOv4 for fire detection. They trained the model using a dataset of both synthetic and real images, achieving high accuracy and recall rates. In another study, Ahuja and Sharma [15] developed a CNN-based model for fire recognition using a dataset of thermal images. The model achieved an accuracy of 95%, outperforming other state-of-the-art models. Additionally, the use of FireWatch, a sensor-based system for fire detection, has also been explored. A study by Narayanan and Thirumalai [16] used FireWatch to detect fire in real time and achieved a high accuracy rate of 98.2%.

Hao *et al.* [17] proposed a novel approach for wildfire detection using deep learning and fuzzy clustering. The method achieved high accuracy and fast detection speed, making it a promising solution for real-time wildfire detection. Zhou *et al.* [18] developed a wildfire detection system based on a CNN and support vector machine (SVM). The system achieved high accuracy and robustness in detecting wildfires, indicating the potential of CNN and SVM in fire recognition. Sun and Feng [19] proposed a fire detection method based on the YOLOv3 network and visual attention mechanism. The method achieved high accuracy in detecting fires from aerial images and demonstrated its effectiveness in real-time fire detection.

Jiao *et al.* [20] proposed an automatic fire detection system based on deep learning for unmanned aerial vehicle (UAV) applications. The system achieved high accuracy and can be used for real-time fire detection in large-scale areas. Huang *et al.* [21] proposed a real-time forest fire detection system based on deep learning. The system achieved high accuracy and can be used in real-time monitoring and early warning of forest fires. Li *et al.* [22] proposed a fire detection method in UAV images based on a region-based CNN. The method achieved high accuracy and robustness in detecting fires from UAV images, indicating the potential of region-based CNN s in fire recognition. In summary, the use of deep learning techniques such as YOLOv4, CNN, and fast R-CNN, as well as sensor-based systems like FireWatch, has shown great promise for fire recognition. Determining the right choice of deep neural network architecture to be used for high fire detection accuracy. In this paper, a comparative analysis was made between deep neural network models.

2. METHOD

One of the modern algorithms for detecting objects in images YOLOv4 [23], [24] can be used to recognize natural fires on satellites and on images from the FireWatch sensor. Improved core network YOLOv4 uses more powerful and DCNNs as the core network for feature extraction from images. The YOLOv4 algorithm is based on CNNs and uses a multi-scale architecture Figure 1 that can recognize objects at different levels of detail.

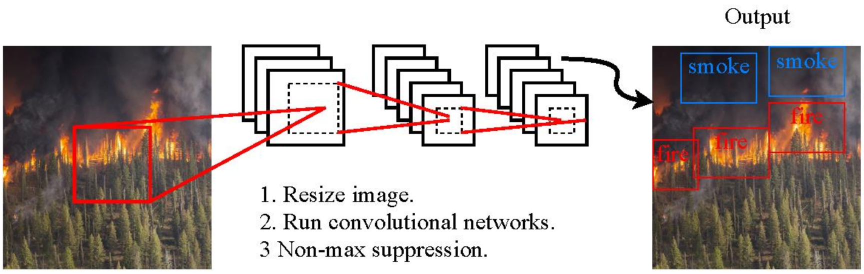


Figure 1. YOLOv4 algorithm architecture

The process of recognizing wildfires on satellite and images from the FireWatch sensor using the YOLOv4 algorithm [25] requires a data set containing images of wildfires and their corresponding markings, that is, the coordinates of the area where the fire is located. It may also be helpful to include images without fires to create negative examples. After data preparation, the YOLOv4 model [26], [27] was trained on this dataset using the backpropagation algorithm. Training is time-consuming and requires high-performance hardware such as graphics processing units (GPUs). After training, the model was tested on new images to determine its accuracy and performance. To test the model, images were entered in which to detect a fire and get a result that will consist of the area where the fire is located and the probability of having a fire in this area.

The fast R-CNN deep learning algorithm is used to detect objects in images. It was used to recognize natural fires both on satellite and on images from the FireWatch sensor. Fast R-CNN Figure 2 uses CNNs to extract features from images. These features were then used to determine the presence of a fire in the image. When testing and validating the model on a variety of data and under various conditions, in order to achieve reliable and accurate fire detection, factors such as lighting, viewing angles, various types of fires, and other factors that affected the performance of the selected YOLO model were taken into account.

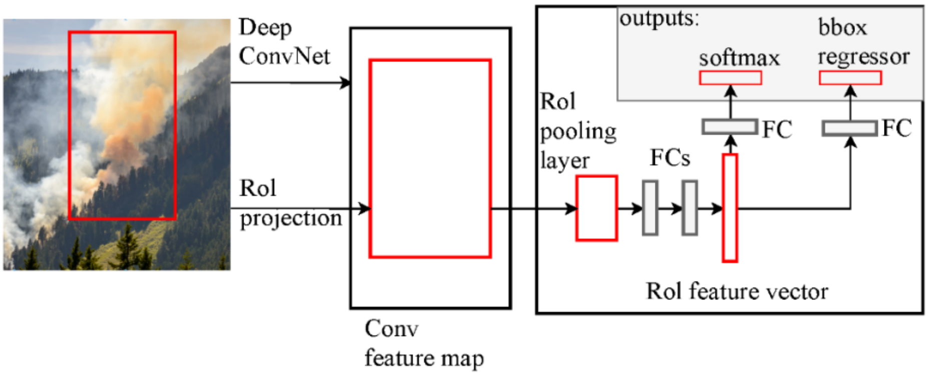


Figure 2. Fast R-CNN algorithm architecture

3. RESULT AND DISCUSSION

To implement deep learning algorithms, satellite images of the Kostanay region of the Republic of Kazakhstan, where there was a fire in the fall of 2022, were taken. The training dataset contains 23,912 pre-trained image sets taken from the Kaggle op database. Figure 3 shows images with and without fire signs.

Figure 3. Normal and abnormal images

In this work, deep learning was performed on satellite and open-source images. During the experiment, the accuracy of identifying anomalous areas in images by algorithms is shown in Table 1. The high accuracy of fire detection in images was shown by the YOLOv4 algorithm in comparison with other algorithms.

The core network of the created application based on the YOLOv4 algorithm runs at 45 fps without batch processing on the GPU i an X, and the fast version runs at over 150 fps. This means that real-time streaming video can be processed with a latency of less than 25 milliseconds. In addition, YOLO provides more than twice the average accuracy of other real-time systems. YOLO thinks globally about an image by making predictions. Unlike methods based on a sliding window and suggesting regions, YOLO sees the entire image during training and testing, so it implicitly encodes contextual information about the classes as well as their appearance. Figure 4 shows the structure of the automated fire detection algorithm based on YOLOv4.

Table 1. Determining fire detection accuracy and learning rate with deep learning algorithms

Map	YOLOv4	SSD	Fast R-CNN
98,9%	830-840	985-990	1000

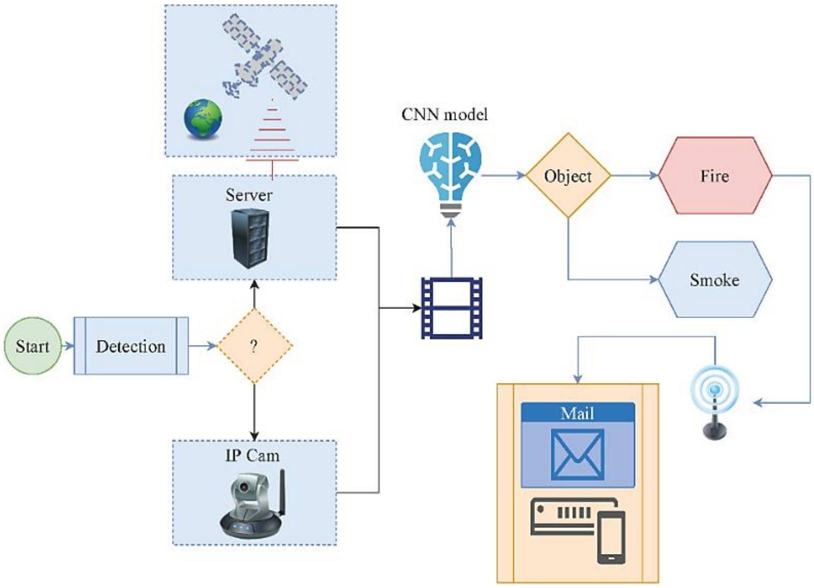


Figure 4. The structure of the automated algorithm

Figure 5 shows the result of the YOLOv4 algorithm for video fire smoke detection. The algorithm can process the video stream in real-time and highlight areas with smoke in images. The model was trained on a large dataset with and without smoke images.

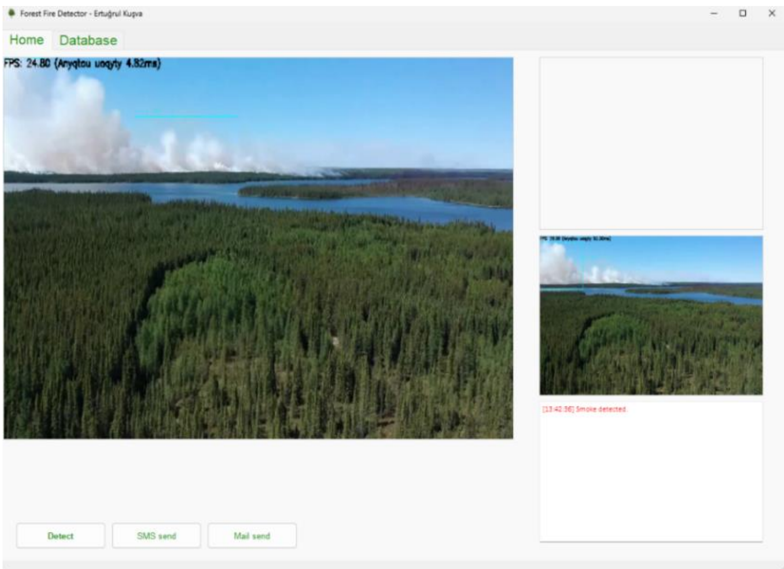
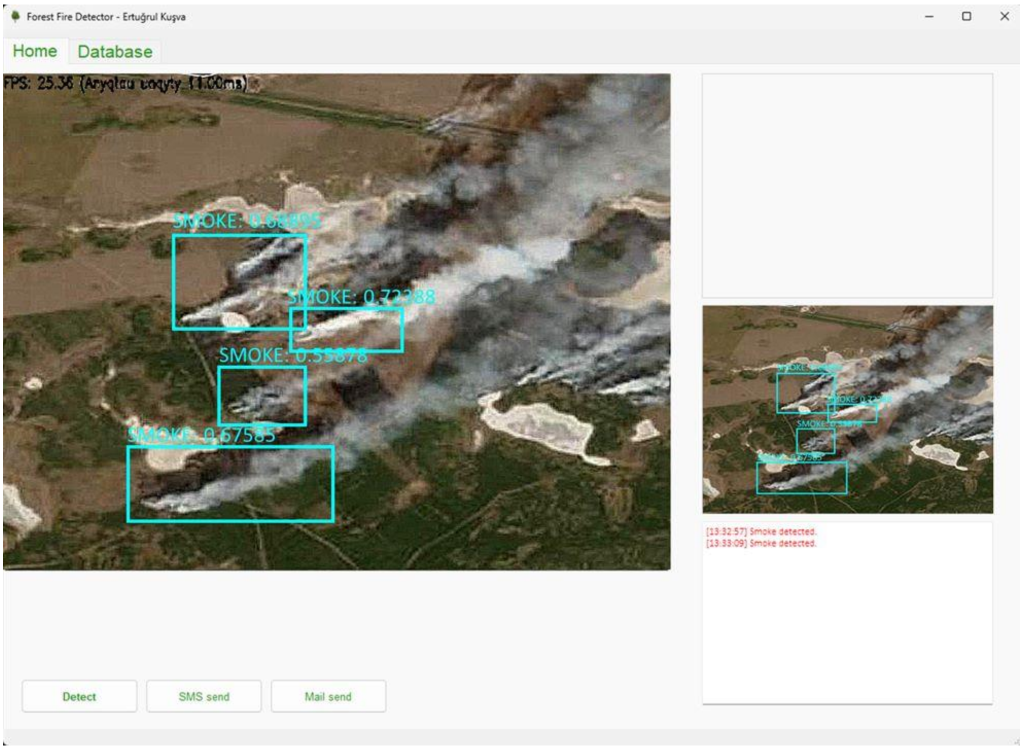
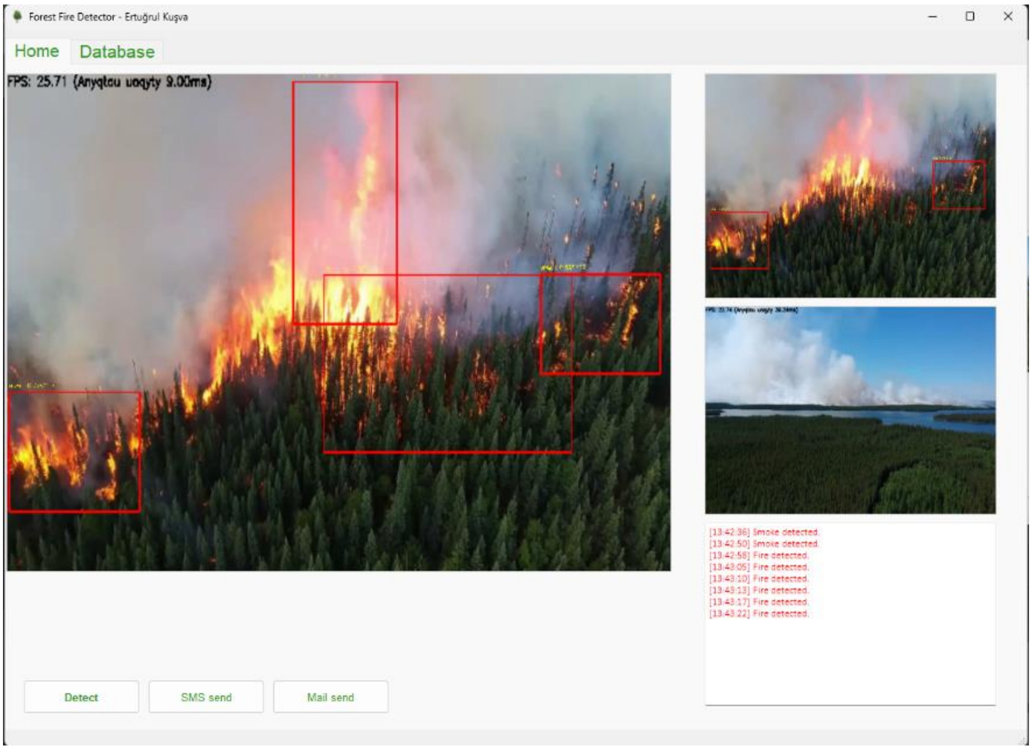


Figure 5. Real-time detection of fire smoke

On Figure 6 shows a nested YOLOv4 algorithm. For the problem of fire detection from space images, the training results are shown in Figure 6(a) and the real-time training results are shown in Figure 6(b). This approach showed high accuracy and speed of image processing. However, the disadvantage may be the complexity of training the model and the need for a large amount of labeled data to train the model.



(a)



(b)

Figure 6. Fire and smoke detection: (a) on satellite images and (b) from real-time image

Figure 7 shows the accuracy of fire and smoke detection training results for each model in graph form. The YOLOv4 algorithm proved to be the most efficient among the deep learning algorithms considered in this study. As a result of the research, YOLOv4 can effectively detect fire and smoke in images in a short period, even when objects are in motion or low light conditions. During the experiment, the detection of fires from satellite images and images from the FireWatch sensor showed its advantages and disadvantages. When detecting a fire, the advantages of satellite imagery are the ability to cover large areas, which allows you to quickly detect fires in remote and hard-to-reach areas, and to obtain a lot of data that have been used to train deep learning algorithms for more accurate fire recognition. And the disadvantages of satellite imagery when detecting fires are the availability only at certain time intervals, which makes it difficult to quickly detect fires. Some types of fires can be difficult to recognize on satellite imagery, such as small fires that quickly extinguish or fires that occur in dense vegetation. Another disadvantage is that satellite imagery can be bulky and require processing and analysis to provide useful information about fires. This takes a lot of time and requires extra effort.

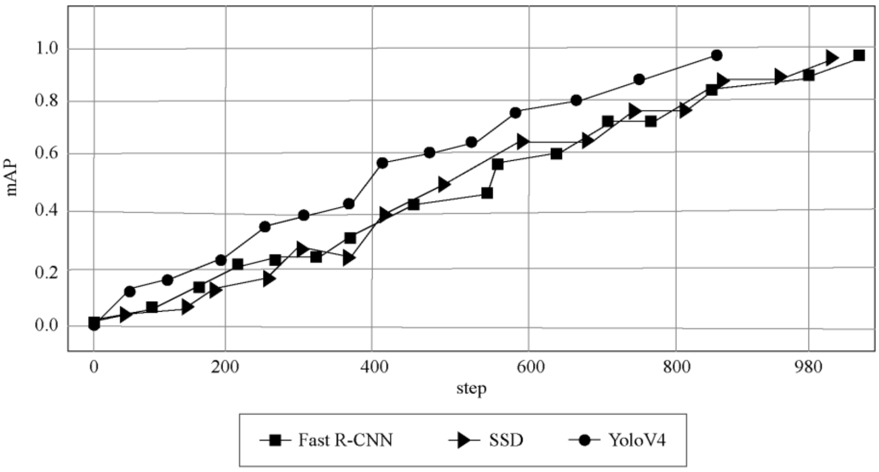


Figure 7. Algorithm training schedule

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When detecting a fire on images from the FireWatch sensor, the advantages are high sensitivity to temperature changes, which would allow the detection even small fires. As well as instant fire detection, which allows you to quickly respond to possible threats. Another advantage of the FireWatch sensor is the low probability of false alarms and reliability in operation. During the experiment, when detecting a fire on images from the FireWatch sensor, such shortcomings were revealed as detecting only those fires that are near the sensor, the high cost of the FireWatch sensor, which limits its use in some cases. Another disadvantage is that the FireWatch sensor does not use optical information, which would be useful for locating and spreading a fire.

4. CONCLUSION

As a result, 3 main methods for recognizing the displayed object data using deep learning were considered, these are YOLOv4, SSD, and fast R-CNN. Thus, the YOLOv4, SSD, and fast R-CNN algorithms turned out to be an effective tool for recognizing forest fires on satellite and images from the FireWatch sensor.

And according to the results achieved when detecting a fire on satellite images and images from the sensor, the YOLOv4 method turned out to be the fastest-real-time object detection. In this paper, the study showed that CNNs show high accuracy in the task of detecting fires and smoke. As a result of this work, datasets containing 2,562 images were used, including fires, smoke, and negative images. The use of the YOLOv4 CNN made it possible to achieve an accuracy of 98.9%. It was used to quickly and accurately detect fires in real-time, which will prevent the spread of fire promptly and protect natural resources.

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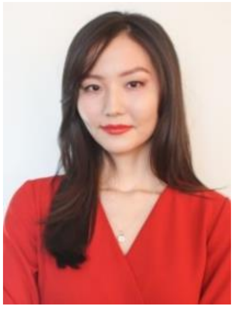

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