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Application of the YOLO algorithm in fire and smoke detection systems for early detection of forest fires in real time

***Abstract**. The paper presents a study of the possibilities of using modern machine learning methods based on the YOLO (You Only Look Once) algorithm in the detection and classification of fire hazards based on camera image recognition. The paper aims to develop an automation system for effectively identifying fire and smoke to develop effective protection of forest complexes. The YOLOv8 model was used in the detection process, which turned out to be a highly effective object detection model in real-time. The paper presents the process of preparing image data sets for the construction of the YOLO model. In the final part of the paper, many tests were carried out to assess the effectiveness and precision of the developed fire detection and fire prediction models. The results of these tests confirmed that the detection model works very precisely and can accurately identify fiery and smoky areas in camera images.*

***Streszczenie.** W pracy zaprezentowano badanie możliwości zastosowania nowoczesnych metod uczenia maszynowego w oparciu o algorytm YOLO (You Only Look Once) w detekcji i klasyfikacji zagrożenia pożarowego na podstawie rozpoznawania obrazu pozyskanego z kamery. Praca ma na celu określenie efektywności działania algorytmu w automatyzacji identyfikacji ognia i zadymienia dla potrzeb opracowania skutecznej ochrony kompleksów leśnych. W procesie detekcji zastosowano model YOLOv8, który okazał się modelem wykrywania obiektów o wysokiej skuteczności w czasie rzeczywistym. W pracy zaprezentowano proces przygotowania zbiorów danych obrazowych dla potrzeb budowy modelu YOLO. (**Zastosowanie algorytmu YOLO w systemach procesu detekcji ognia i zadymienia dla potrzeb wczesnego wykrywania pożarów leśnych w czasie rzeczywistym**)*

Keywords: YOLO, Fire detection, Deep learning, Computer vision..
Słowa kluczowe: YOLO, wykrywanie pożaru, głębokie uczenie, analiza obrazów.

Introduction

One of the main environmental protection problems are forest fires, which lead to the degradation of forest ecosystems and have far-reaching economic and ecological consequences and have a negative impact on biodiversity [1]. Fires threaten the safety of people, animals and infrastructure. Forest fires contribute to the emission of significant amounts of carbon dioxide and other greenhouse gases, which contribute to global warming. Currently, the annual area of burned forests is from 300 to 600 million hectares. About 90% of this area is the result of 5-10% of the largest fires [2].

Due to the growing fire threat and its impact on the climate and greenhouse gas emissions, it is necessary to take preventive measures. Quick response and effective fire extinguishing are key to forest protection. For this reason, there is a growing need to develop modern, reliable systems for early fire detection. As part of the "Fit for 55" legislative package presented by the European Commission [3], EU countries will receive new tools to support efforts to reduce greenhouse gas emissions. The package includes changes to the emissions trading system, directives on renewable energy sources and energy efficiency, and places particular emphasis on forest management and land use. The European Commission indicates that 43.5% of the EU land area (approx. 182 million hectares) is forests and other wooded land [4], which play a key role in absorbing greenhouse gases.

In March 2023, the EU Council adopted regulations on effort sharing and the land use and forestry sector (LULUCF), enabling the EU to reduce net greenhouse gas emissions by at least 55% by 2030 compared to 1990's levels. The ESR regulation assumes a 40% reduction in emissions by 2030 compared to 2005. LULUCF is to support the achievement of climate goals through net absorption of greenhouse gases. By 2030, Member States will have national targets for increasing the absorption of greenhouse gases, which will allow for achieving a common EU net absorption target of 310 million tonnes of CO_2.

In Poland, forests cover about 30% of the country's area, and their role in CO_2 absorption is significant. They absorb about 40 million tonnes of this gas annually, which is an important element of the national climate policy.

Assuming in the calculations according to [5-10] for Poland that the annual absorption of CO_2 by forests is in accordance with the geomechanical model of CO_2 absorption and that the price of one ton of CO_2 on the market is 70-90 Euro with a weighted average of 83.85 Euro in 2023, the economic value of this absorption may amount to approximately 2.1 billion Euro.

Forest fires are an important element in the global CO_2 emission balance. It is estimated that about 10% of the total carbon dioxide emissions in the world come from forest, savannah and other biomass fires. This means that emissions from forest fires may significantly affect the balance of CO_2 absorption by forests.

On the one hand, forests absorb about 7.6 billion tons of CO_2 per year, which is a significant part of the total global emissions from human activity [11]. Forest fires release stored carbon back into the atmosphere. Emissions from biomass fires (including wildfires 1 to 2 billion tons of CO_2 per year) can amount to 1 to 5.7 billion tons of CO_2 per year [12], which significantly reduces the net capacity of forests to absorb CO_2. Compared to emissions from wildfires, forest fires are responsible for about 13-26% of the amount of CO_2 absorbed by forests. Early fire detection allows for a faster response, which is crucial for protecting forest ecosystems from the catastrophic effects of fires. For this reason, automation of fire threat detection using various techniques and technologies can significantly support environmental protection and the achievement of global climate goals. YOLO (You Only Look Once) algorithms are crucial for protection, especially in the context of early fire detection and monitoring of the forest environment. As one of the fastest and most effective detection algorithms, YOLO can be used to analyze images from drones, stationary cameras or satellites to quickly identify threats such as smoke or fire.

Related Works

In the literature, various methods for fire identification are presented based on smoke detection such as shape, colour, texture and motion features. In the papers [13-16] authors used the colour-based detection of smoke areas. Other methods are based on smoke detection based on its motion and colour features. In [17] authors proposed a method that uses an optical flow and backpropagation neural network for smoke classification. Colour data can also be used to develop a smoke detection system. In the papers [13, 16, 18] a smoke detection technique using C-mean blur for clustering and backpropagation neural network for smoke classification was presented. Another approach is analyzing of various shape features, including contours, edge orientation histograms, spectral, spatial and temporal characteristics of smoke [19]. Other proposed solutions were presented in [20] based on the model of movement orientation and approximate median. In [21,22], an approach based on methods based on texture features was used, including the local binary pattern.

In the case of forest fire detection, systems based on artificial intelligence allow for the analysis of images from cameras in real-time and automatic detection of anomalies, including fire and early warning [23, 24]. Such systems can also distinguish different types of smoke [14], [25-27] or other factors that detect fire at its early stage. Thanks to the use of machine learning algorithms, these systems are able to accurately analyze images and detect objects, even in difficult weather conditions or with limited visibility.

YOLO algorithm as the automated forest fire detection method

The YOLOv8 (You Only Look Once) architecture was used to create a fire detection model. It provides high accuracy in object detection, which is crucial for precise detection of forest fires. The YOLOv8 Small model was used in the detection process, which turned out to be one of the most effective models for real-time object detection, even though there are other versions, including YOLOv11 [28]. The YOLOv8 architecture offers the ability to detect multiple objects at the same time, which is useful in situations where there may be multiple fire outbreaks in the image. This method of object detection in images is characterized by a single image review. It means that the entire image is analyzed simultaneously to detect and localize objects, unlike other methods that rely on image processing in multiple steps. YOLO uses an innovative neural network architecture [26-33] that simultaneously predicts bounding boxes and object class membership. The image is divided into a grid of cells, and for each cell, several bounding boxes and probabilities of belonging to different classes are predicted. Thanks to this approach, YOLO achieves very high speed, enabling real-time object detection. In addition, a single image review allows for taking into account the global context, which can improve the accuracy of object localization. The graphical scheme of the single image review can be seen in Figure 1.

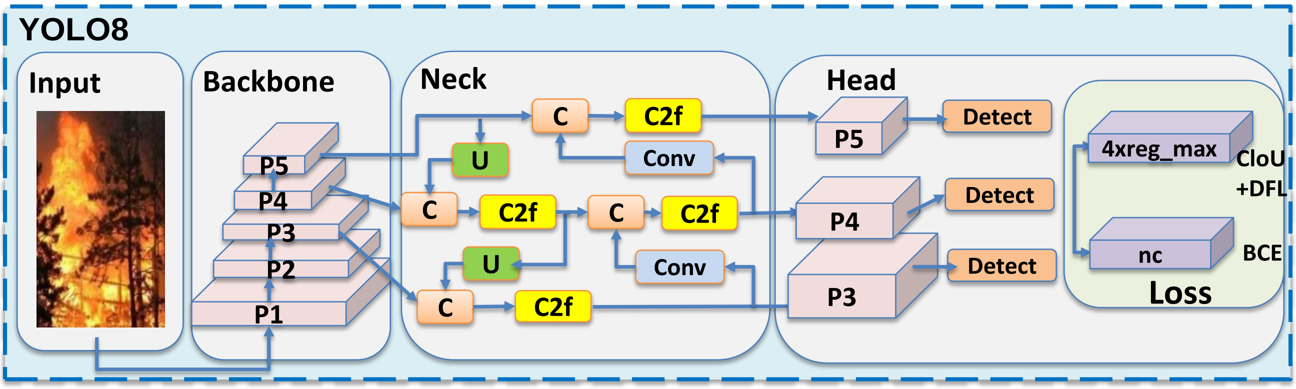

Fig.1. Graphical diagram of the operation of a single image review

YOLOv8 is an advanced model that requires significant computing power for effective training. The GPU offers parallel processing, which allows for accelerating the training process by simultaneously performing multiple operations on training data. Compared to traditional CPUs, the GPU can be up to several hundred times faster, which translates into a significant reduction in model training time. The GPU allows for efficient processing of this data, which is crucial for obtaining high-quality models. This allows the model to be trained on larger data sets, which leads to better generalization and more accurate object detection. To take advantage of GPU processing in YOLOv8, it is necessary to meet certain hardware requirements (NVIDIA GeForce card with CUDA architecture support required) and appropriate software configuration.

YOLOv8 is an innovative and efficient neural network that differs from traditional object detection models. It is fully convolutional, which means that it does not use fully connected layers. This makes it faster and more suitable for applications in real-time systems. The YOLOv8 network works iteratively, performing only one propagation through the network to perform detection. This significantly speeds up the process and allows it to operate efficiently in real-time. As a result, the network performs multiple (usually four-fold) size reduction, transforming an input image of, for example, 640x640 pixels to an output of 80x80. In particular, the YOLOv8 architecture uses more advanced layers, such as CSP (Cross Stage Partial) and SPP (Spatial Pyramid Pooling), to optimize the feature extraction and detection process.

Data preparation process for the YOLO algorithm

During object detection, YOLOv8 operates on images of different sizes and aspect ratios. However, to enable parallel processing in the neural network, all images must have the same input dimensions. For this purpose, edge padding is used, which consists of adding additional pixels to the edges of the image to bring it to a specified, uniform size. These pixels have a zero value, which means that they will not provide additional information about the objects in the image. Zero padding is important because it allows for maintaining consistency of dimensions in the neural network and the applied convolutional layer will not reduce the size of the image. The consequence of the convolutional layer is the normalization layer (batch normalization). The batch normalization layer (BN) is used in neural networks to regulate the distribution of activation values on individual layers. The normalization layer works by scaling and shifting the feature values so that they have a mean of zero and a variance of one. In practice, the mean and standard deviation are calculated for each feature in a given batch. Then, the feature values are rescaled and shifted using the calculated parameters to meet the desired normalization criteria. In the case of YOLOv8, the use of the BN layer contributes to achieving high object detection accuracy and increased model performance. Figure 2 shows a simplified scheme of the neural network operation. The dataset used was taken from the site [34] and contained 6.6 thousand images, with annotations (on the location, size and other fire features) of data for model training, 1886 validation images and 943 images for the testing process.

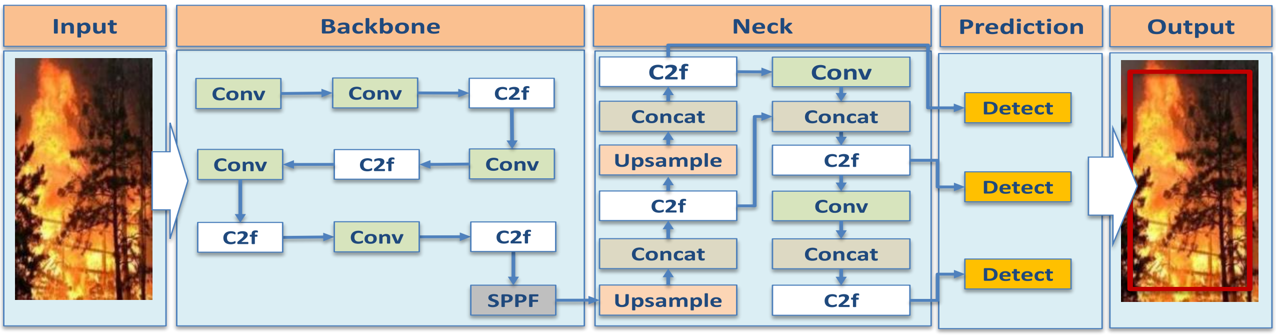

Fig.2. Simplified diagram of a neural network work

Analysis and Simulation

When training a neural network, the goal is to find the optimal weight values that minimize the cost function. This process involves adjusting the network weights in such a way as to reduce the error between the predicted and actual network results. Iteratively calculating gradients and updating the weights allows to find the best parameters that allow the network to achieve the highest efficiency and accuracy in the performed tasks. The cost function itself in detection problems is more complicated compared to the classification problem. In the case of YOLOv8, the following cost function was used:

$$\min_{\theta} L(\theta, X, Y) \tag{1}$$
$$L = L\{x,y\} + L\{w,h\} + L\{obj\} + L\{noobj\} + L\{class\}$$

where:
θ – parameters of the NN (weights and biases)
X – annotations and classes returned by the network
Y – annotations and classes defined in the training set
L{x,y} – localization error for object coordinates
L{w,h} – error in object dimensions
L{obj} – detection error in the presence of an object
Lnoobj – detection error in the absence of an object
Lclass – classification error

The model training process took 1.5 days, which is in line with expectations and results from the number of training files as well as the complexity of the model. The GeForce RTX 4070 graphics card was used in the process of creating the detection model, which allows for the effective use of the GPU computing power.

Results

Thanks to the use of GPU, it was possible to accelerate the calculations related to the training process, which allowed for achieving satisfactory results. Tests were carried out on random images and the results of these tests turned out to be very promising. The YOLOv8 detection model showed high effectiveness in identifying objects related to fire, such as fire and smoke. Detection worked properly, and the results met the expectations. The model was able to precisely locate fires in images, which is key information for monitoring and rapid response. Figure 3 shows an example of the detection of the prepared model in finding fire and smoke objects on one of the images used for testing.


Fig.3. Detection of fire (red frame) and smoke based on the image

Conclusions

The use of the YOLOv8 algorithm proved to be very effective in detecting fire and smoke in images for the implementation of real-time early warning systems for forest fires. The developed YOLOv8 model showed high precision (87.5%) and sensitivity (81%) in identifying fire hazards, which ensures very effective, early detection, which is crucial for a quick response. The YOLO architecture, which allows for the analysis of the entire image in a single pass, allowed for obtaining fast detection results at the level of 106 frames per second, which is important for real-time monitoring in the forest environment. Additionally, the results confirmed that the model is suitable for practical use, taking into account balanced performance indicators, including an F1-score (harmonic mean of precision and recall) of 84.1%.

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