Method of early landfill fire detection using the YOLOv8 neural network

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Abstract

In addressing the challenge of early landfill fire detection using external surveillance cameras, this study proposes a method leveraging the YOLOv8 neural network model. An experiment was conducted utilizing the YOLOv8-s variant trained on the Roboflow dataset, with performance evaluated through precision, recall, and F1 score metrics. The results demonstrated an average precision of 0.93707, indicating that the model correctly identifies objects 93.7% of the time, thereby maintaining a low false positive rate. Additionally, the model achieved a high recall of 0.9061, successfully detecting 90.6% of actual objects and exhibiting a low false negative rate. The F1 score was 0.9213, reflecting a balanced trade-off between precision and recall. These metrics collectively suggest that the YOLOv8 model is both accurate and robust, making it a reliable tool for early detection tasks. The promising results underscore the model's potential for real-world applications where high accuracy and reliability are essential. Future work will focus on developing an information system for early landfill fire detection based on the method proposed in this study.

Keywords

Image processing, landfill fire detection, neural networks, YOLOv8

1. Introduction

Fires in solid waste landfills are a significant hazard due to the large impact on the environment, health and safety and can even cause loss of life. During a fire in Hrybovychi, Lviv region, Ukraine [1-3] in 2016, three rescuers died, and a significant amount of harmful substances were released into the air. Another large-scale fire occurred in 2023 on the plain [4]. However, this time, fortunately, the death of people was avoided.

Fires at solid waste landfills are among the most complex and long-lasting, extinguishing which requires the involvement of significant resources, efforts, means and time. Forecasting and prevention of fires at landfills is extremely complicated, as it is difficult to determine possible centers of temperature increase due to different specific heat capacities of waste. Until

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the fire or smoke has reached the surface, it is almost impossible to detect the source of ignition visually. Fires mainly occur during the fire-hazardous period in the summer. The main cause of fires remains human imprudence and carelessness, neglect of fire safety rules, careless handling of fire, violation of technological regulations for disposal of solid household waste. Landfills are capable of spontaneous combustion. The process is caused by the biochemical decomposition of waste, which is accompanied by an increase in temperature to 40-70 °C.

The main causes of landfill fires include:

1) Decomposition heat - organic materials in landfills decompose, producing heat. When this heat accumulates without adequate ventilation, it can ignite surrounding waste.
2) Chemical reactions - certain chemicals and materials can react exothermically, generating heat and potentially leading to combustion.
3) Human activities - careless disposal of lit cigarettes, fireworks, or other flammable items by individuals can start fires.
4) Arson - intentional setting of fires, whether for malicious purposes or to reduce waste volume.
5) Faulty equipment - malfunctioning machinery or exposed electrical wiring can create sparks that ignite flammable materials.
6) Overheating - overloaded electrical systems in or near the landfill can overheat and cause fires.
7) Gas build-up - methane, produced by the anaerobic decomposition of organic waste, is highly flammable. Without proper gas collection systems, methane can accumulate and ignite.

The consequences of the fires that happen on landfills are the following:

1) Air pollution - burning waste releases toxic smoke and harmful pollutants such as dioxins, furans, and particulate matter, contributing to air quality degradation and respiratory health issues.
2) Greenhouse gas emissions - fires release large amounts of CO2 and other greenhouse gases, exacerbating climate change.
3) Soil and water contamination - ash and residues from fires can seep into the soil and groundwater, contaminating local water supplies and harming ecosystems.
4) Health risks - respiratory problems: exposure to smoke and toxic fumes can cause acute respiratory issues, exacerbate chronic conditions like asthma, and increase the risk of long-term health problems such as lung cancer.
5) Chemical exposure - communities near landfills are at risk of exposure to hazardous chemicals released during fires, which can lead to various health complications.
6) Firefighting and cleanup -extinguishing landfill fires and managing the aftermath require significant financial resources, manpower, and time.
7)Property damage - fires can spread to nearby areas, damaging infrastructure, properties, and agricultural land, resulting in economic losses.
8)Landfill closure - ongoing fires can force landfills to temporarily close, disrupting waste management services and creating additional public health and environmental challenges.

9)Rehabilitation costs - post-fire site rehabilitation to ensure the area is safe for future use can be expensive and time-consuming.
10) Public safety concerns - evacuations: severe landfill fires may necessitate the evacuation of nearby communities to protect residents from harmful smoke and fumes.
11) Long-term exposure risks - prolonged exposure to pollutants from recurring landfill fires can lead to chronic health issues for local populations.

This research focuses on the Sustainable Development Goals (SDGs)[5] established by the United Nations (UN) and adopted by all UN Member States in 2015. Specifically, it addresses SDG 12: Responsible Consumption and Production, and SDG 15: Life on Land. Landfill fires pose significant and undeniable harm to all living beings on Earth [6], therefore the problem of landfill fires early detection is quite relevant for faster disposal and prevention of emissions of harmful substances into the air and human casualties.

2. Related works

During the study, an analysis of the most recent scientific publications on early landfill fire detection was conducted. The research [7] helps to detect the gases emitted from garbage, with the project's importance increasing due to the rise in solid waste. The purpose of [8] is to highlight the issue of landfill fires and their effects on air, soil, and water, drawing from a review of documented fires and fire indicators in the areas where the authors conducted their research. The goal of the study [9] was to determine the exact temperature at which each waste kind ignites and maintains smoldering, which would aid in proactive fire prevention and effective waste management. The study [4] compares the output and underlying assumptions of each model and suggests the FODM and LandGEM SP simulations can be suitable for estimating methane emissions in the conditions of Khulna. The study [5] concentrates on developing a methodology to create 3D thermal models by projecting TIR image data onto a 3D model generated from RGB images and identifying thermal anomalies using photointerpretation and GIS analysis. This source [6] proposed a comprehensive method for PFAS screening in leachate samples using suspect and nontarget analysis. The study [7] presents a developed methane emission model which can be replicated globally. The research [8] focuses on managing leachate by recirculating the nutrient-rich fluid back into the landfills, transforming them into bioreactors. This approach maximizes landfill performance parameters, making them more efficient for electricity production in waste-to-energy plants. The paper [9] presents an experimental investigation into the physio-chemical properties of landfills by recirculating leachate to achieve sustainable performance characteristics in landfill models. The study [10] aims to explore various aspects of mine fire data using CatBoost and LightGBM methods to reduce human fatalities and material losses during the construction of deep underground engineering projects. The study [11] highlights effective solid waste management practices and discusses ways to manage it sustainably through resource recovery. The work [12] aims to predict the fire danger rating of underground mining production processes by applying advanced unsupervised and supervised machine learning techniques. The study [13] introduces a transparent decision-making framework for landfill site selection that combines multi-criteria decision making, fuzzy set theory, GIS and eXplainable Artificial Intelligence (XAI). This study [14] includes an analysis of various machine learning (ML) algorithms for municipal solid waste management to improve procedures and mitigate adverse environmental impacts. The paper [15] discusses an innovative application of dioxin-like persistent organic pollutants (dl-POPs) emission trends as a measure of environmental performance for designing effective municipal solid waste management (MSWM) schemes.

The publications analyzed above consider the probability of occurance fires on the landfills and estimate the emissions of harmful substances into the air and the amount of air and land pollution caused by the degradation of household waste on the landfills. These studies have merely theoretical background and do not propose early fire detecting methods.

The works [22], [23] propose the application of machine vision, namely pattern recognition using artificial neural networks for finding free parking spaces. In [24], the application of the YOLOv8 model is proposed for automating the security of warehouses using images from outdoor surveillance cameras.

Therefore, taking into account the abovementioned analysis and based on the comparative analysis of machine learning methods and technologies in [23] and [24], it was decided to apply the YOLOv8 artificial neural network model for learning fire and smoke recognition for the purpose of early detection of fires in landfills.

3. Dataset preparation and model selection for the implementation

For the early detection of landfills fires, a method of recognizing smoke and fire images from outdoor surveillance cameras using machine vision was chosen. Since the task before us is the task of image classification, that is, trying to predict whether there is smoke or fire in the image or not. For the task of classification, the supervised learning method is best suited. Supervised learning is an approach to machine learning defined by using labeled datasets to train algorithms for data classification and outcome prediction.

A labeled data set has an output labeled with tags corresponding to the input data so that the machine can understand what to look for in the unseen data. The working principle of the supervised learning method is presented in Figure 1.

Data preparation is one of the most important steps in the neural network training process [27]. The accuracy and efficiency of the model depends on training data quality. Especially, at the stage of data collection, attention should be paid to:

- Volume of data. Typically, the more data used, the better the model can be trained;
- Data quality. The data must be accurate, complete and representative of the problem to be solved;
- Variety of data. It is important that the data set contains examples from all possible categories or classes that the model will need to recognize.

Neural network developers often list their guidelines for dataset preparation. In particular, the developers of the YOLO neural network provide the following recommendations [28] regarding data preparation:

- number of images per class: >=1500.
- number of copies (objects with labels) per class: >=10000.
- background images: 0-10% of the total amount.

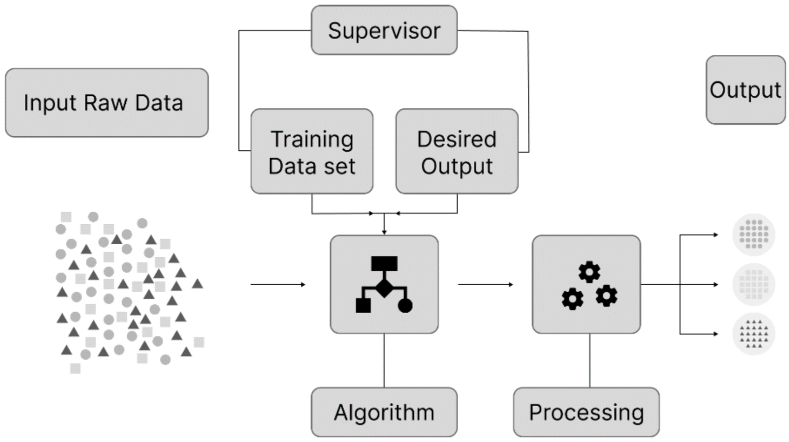


Figure 1: The working principle of the supervised learning method [25].

In addition to quantitative recommendations, there are others, in particular:

- Variety of images. For cases of real use, it is recommended to use images obtained at different times of the day, different seasons, different weather, different lighting, different angles, from different sources (cameras), etc.;
- Marking sequence. Every occurrence of every class in all images needs to be labeled. Incomplete labeling is not sufficient;
- Marking accuracy. Labels should tightly cover each object. There should be no gaps between the object and its bounding box.

The prepared data should be divided into 3 groups:

1) Training set - the dataset used to train the model.
2) Verification (validation) set - the dataset is utilized to assess the model's performance throughout the training process.
3) Test set - the data set used to finalize the model's performance after training is complete.

The ratio between these sets is determined as follows: as a rule, 10-20% of the total volume of prepared data is allocated to the validation and test sets, and 80-60% to the training set, respectively. These parameters can vary, even go beyond the mentioned limits, depending on the total size of the prepared data, the complexity of the model, the used training hyperparameters, as well as the subject area of use of the trained model.

Since this study pursues a specific goal, namely the detection of ignition in landfills, the Roboflow dataset [26] was chosen for training the neural network. It contains 9686 images with two classes - smoke and fire, and split for training, validation and testing.

An example of an image from the Roboflow dataset is presented in Figure 2.

Other images from this dataset that were used for the neural network model training are presented in Figure 3.

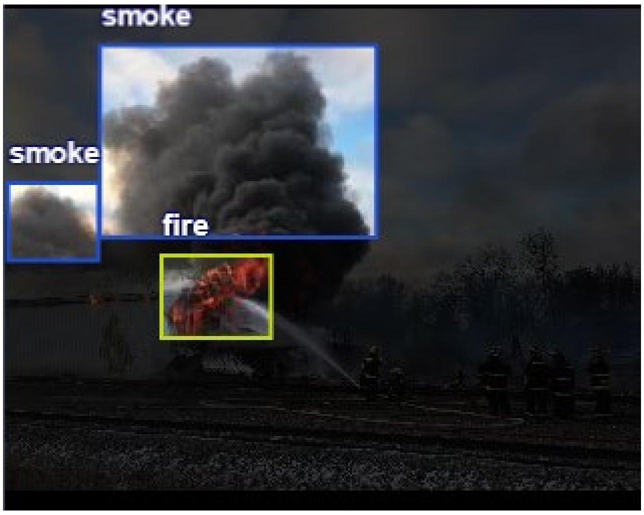


Figure 2: An example of an image with “smoke” and “fire” classed from the Roboflow dataset [26].

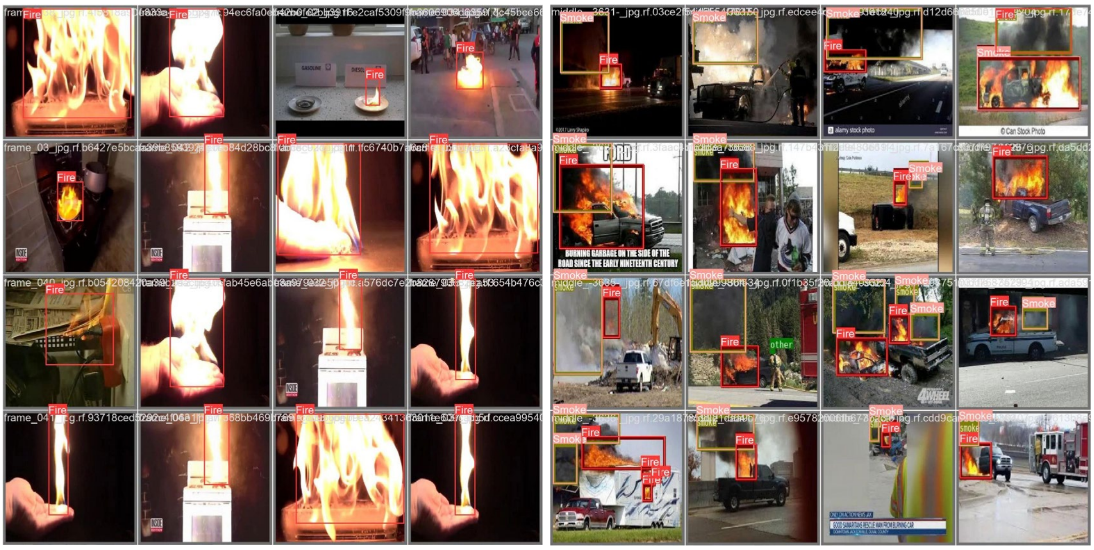


Figure 3: An example of the the images for neural network model training from the Roboflow dataset [26].

4. Method of early landfill fire detection using the YOLOv8 neural network

Method of early landfill fire detection using the YOLOv8 neural network consists of the following steps:

1. Preparation and training of a neural network model on a dataset with "smoke" and "fire" classification.
2. Validation of the neural network model on real images of fires at landfills.

3. Automatic detection of fires at landfills in videos from outdoor surveillance cameras and saving images using the existing YOLOv8 model using Python program.
4. Manual verification of recognition results, separation of cases of false detection of fire or smoke.
5. Evaluation of the automated detection quality.
6. Manual labeling of incorrectly processed images.

The method is visually represented in Figure 4.

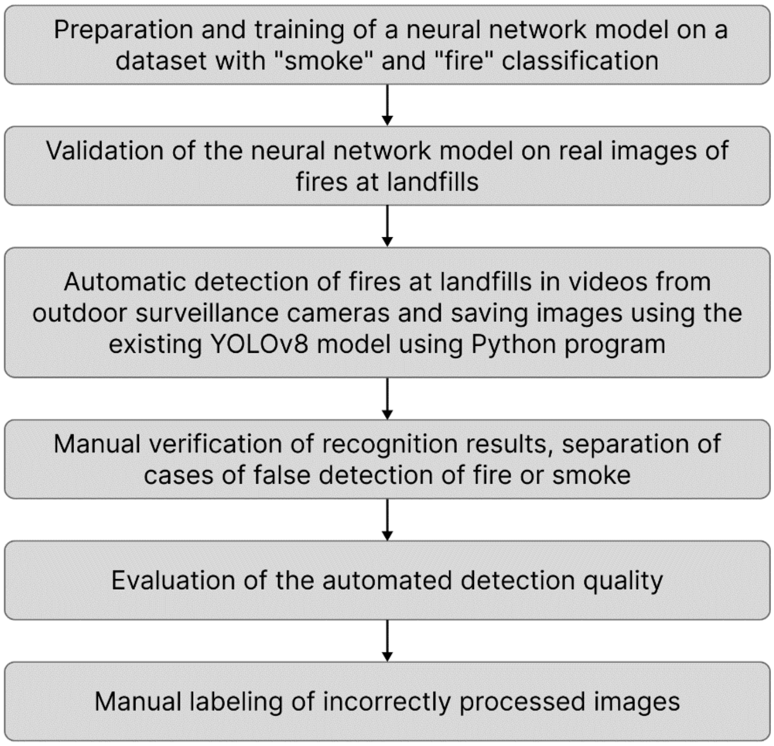


Figure 4: Visual representation of Method of early landfill fire detection using the YOLOv8 neural network.

5. Experiments and Results

To conduct the experiments, the YOLOv8 neural network model was trained on the Roboflow dataset for 125 epochs.

The training results are presented in Table 1.

The table shows that already at the 125th epoch, the train/box_loss and train/dfl_loss indicators begin to decrease, so further training is not effective.

We have reached the maximum indicators.

Evaluation of training results was carried out in 2 ways: using the obtained metrics which is presented in Figures 5-8, and manually (saving data from the video using the newly created model, manually searching for erroneous results).

Table 1
Results of YOLOv8 training on Roboflow "smoke" and "fire" dataset

Epochs	train/box_loss	train/dfl_loss	metrics/precision(B)	metrics/recall(B)	metrics/mAP50(B)	metrics/mAP50-95(B)	val/box_loss	val/cls_loss	val/dfl_loss	lr/pg0	lr/pg1	lr/pg2
1	1.5535	2.159	1.617	0.77306	0.72605	0.7791	0.6103	1.0377	0.96471	1.3708	0.003326	0.003326
2	1.3999	1.4612	1.4798	0.84439	0.75075	0.83226	0.66328	1.0041	0.99759	1.3348	0.006607	0.006607
3	1.4372	1.5241	1.512	0.8035	0.77583	0.82885	0.65468	1.0295	1.0433	1.3554	0.009835	0.009835
4	1.5073	1.6159	1.5615	0.778	0.77058	0.82869	0.6481	1.0298	1.0531	1.3595	0.009762	0.009762
5	1.4677	1.5333	1.5346	0.86732	0.80798	0.85985	0.69135	0.94868	0.87123	1.307	0.009683	0.009683
6	1.443	1.4798	1.5262	0.83168	0.8007	0.86069	0.69606	0.97722	0.94286	1.3246	0.009604	0.009604
7	1.414	1.4146	1.5109	0.87346	0.84093	0.86637	0.71764	0.9003	0.80314	1.2951	0.009525	0.009525
8	1.4014	1.387	1.4966	0.89735	0.8526	0.88055	0.73037	0.88859	0.80101	1.2676	0.009446	0.009446
9	1.3741	1.3401	1.4791	0.90382	0.85454	0.89724	0.7496	0.85062	0.73299	1.2328	0.009366	0.009366
10	1.3315	1.302	1.459	0.89978	0.83883	0.88761	0.75338	0.85226	0.70544	1.2372	0.009287	0.009287
…	…	…	...	…	…	…	…	…	…	…	….	…
123	0.69156	0.38405	1.005	0.90633	0.88936	0.92104	0.84159	0.5755	0.40456	1.0956	0.000338	0.000338
124	0.68591	0.37955	1.0044	0.89673	0.89798	0.92115	0.84208	0.57613	0.4047	1.0963	0.000258	0.000258
125	0.68454	0.37691	1.0016	0.89841	0.89802	0.92117	0.84177	0.57585	0.40565	1.096	0.000179	0.000179

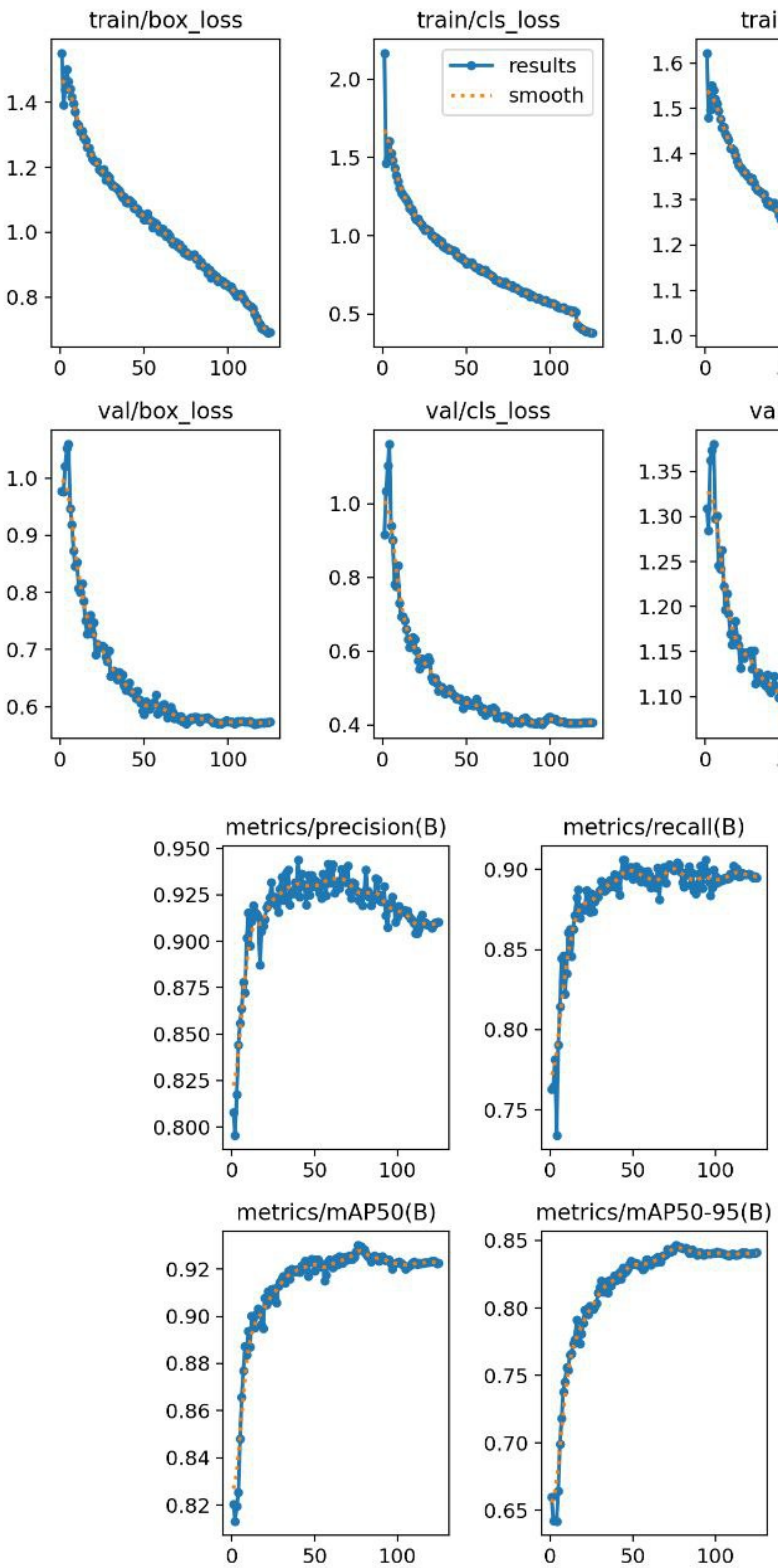


Figure 5: Metrics for training results evaluation.

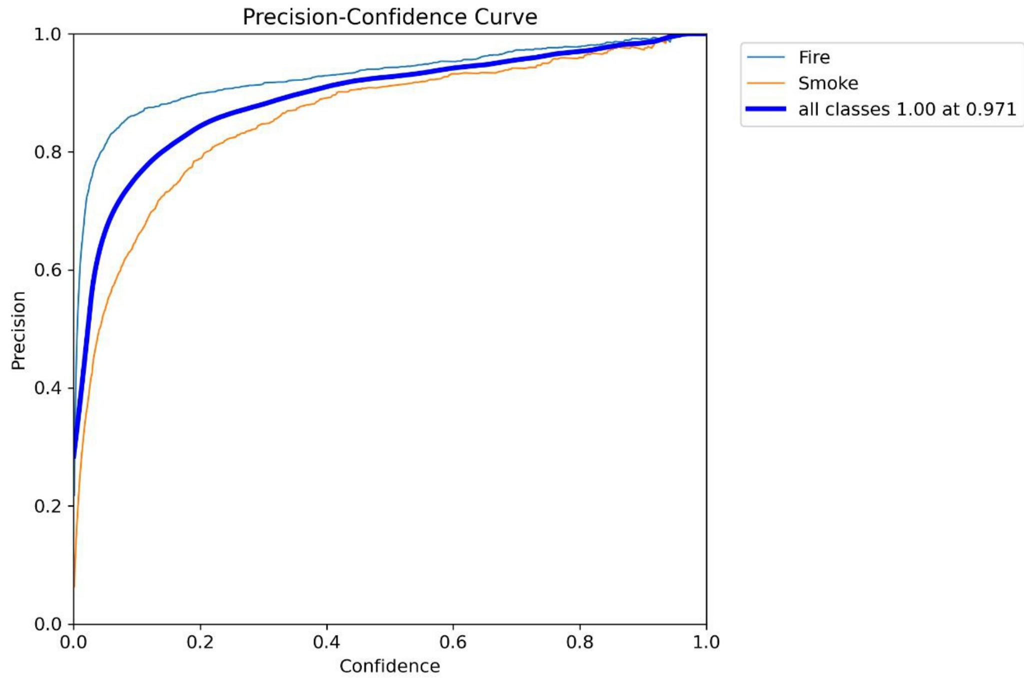


Figure 6: Precision-Confidence Curve.

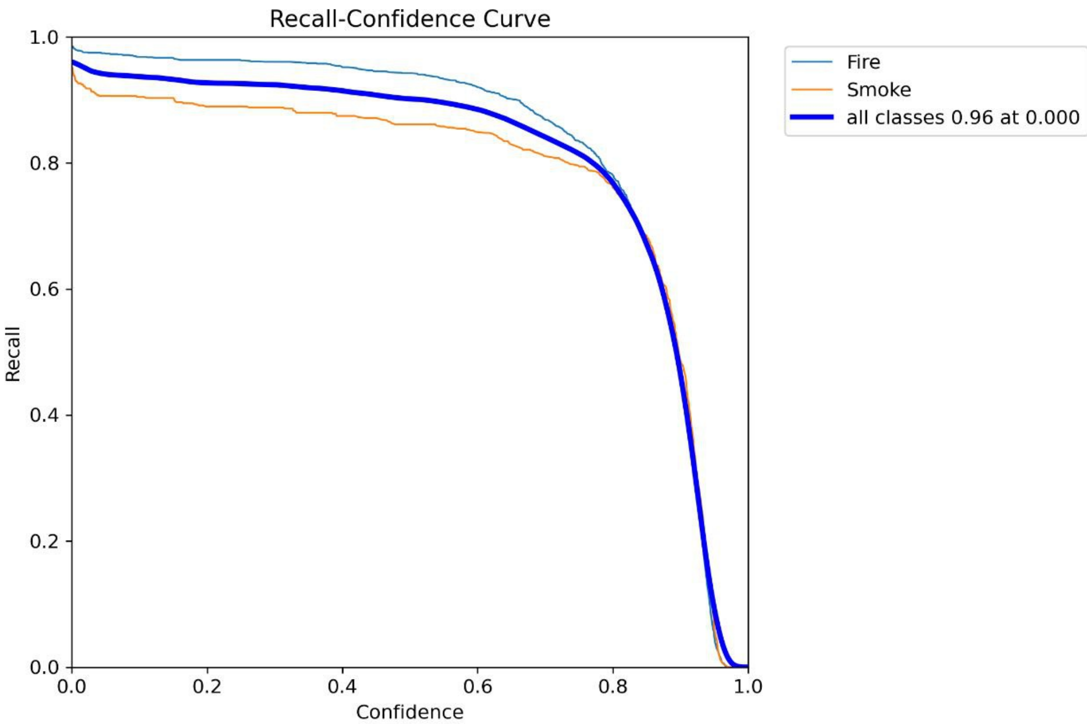


Figure 7: Recall-Confidence Curve.

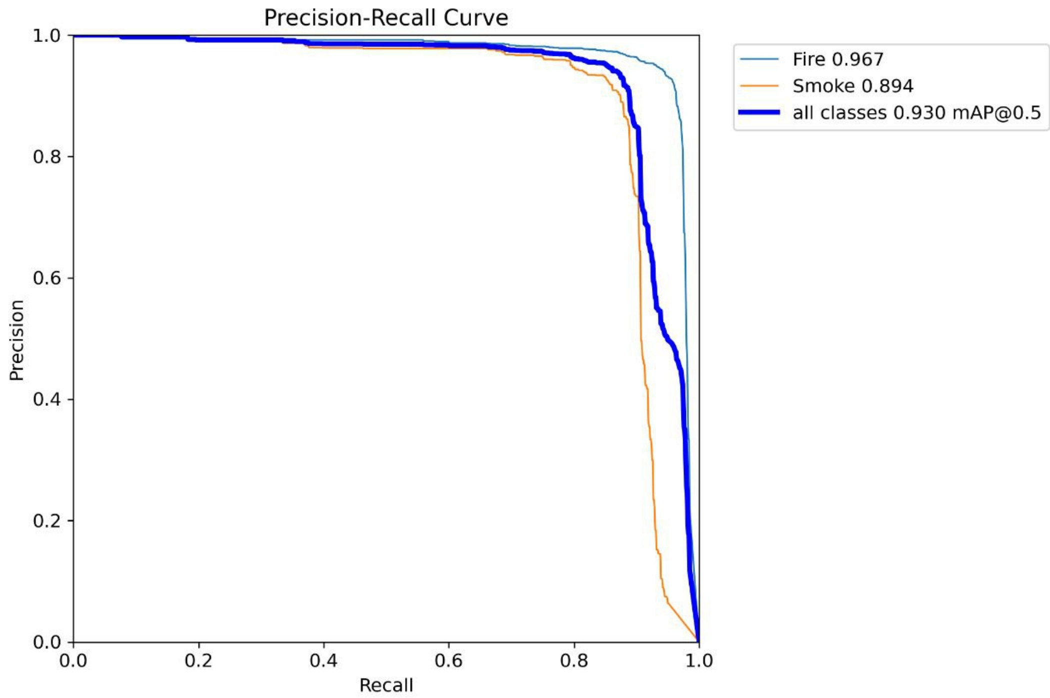
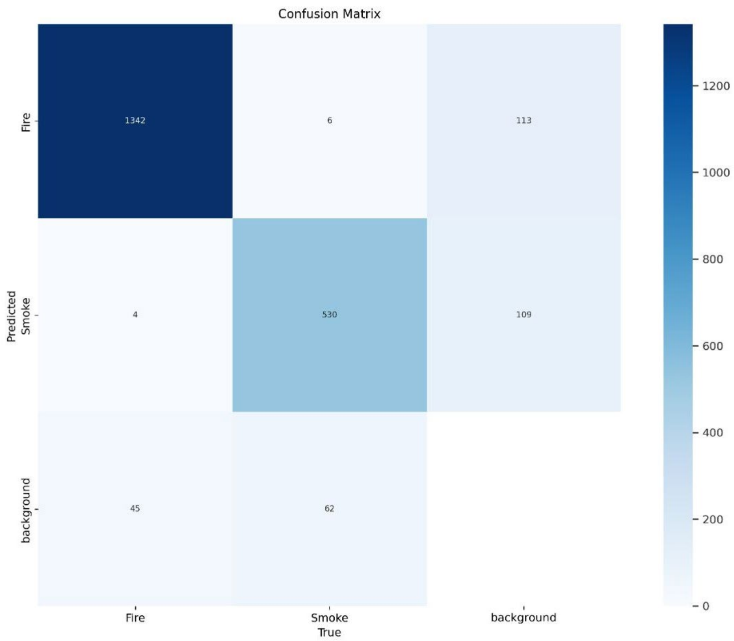
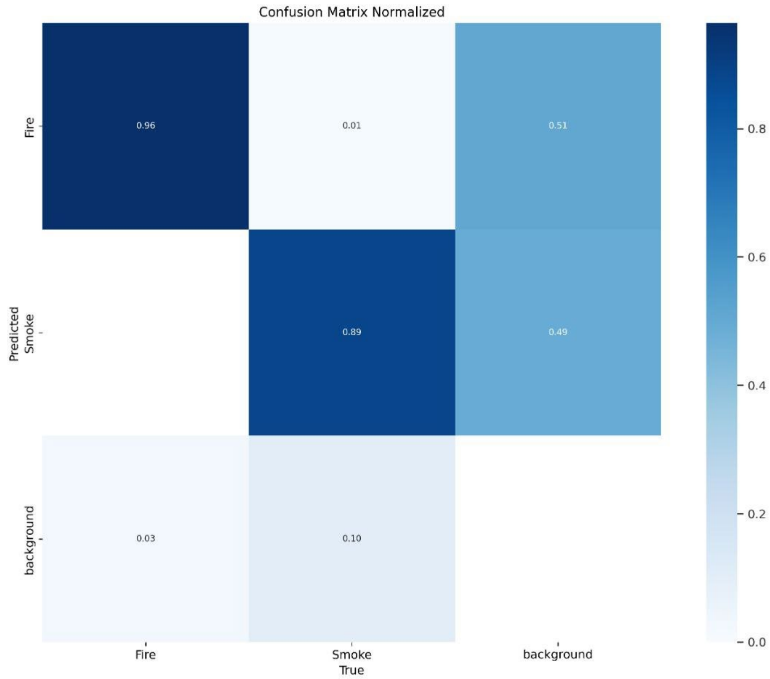


Figure 8: Precision-Recall Curve.

Figure 9 presents confusion matrix in numerical (a) and in percentage (b) ways. The results of images from Roboflow dataset verification in which the neural network detected smoke and fire are presented in Figure 10. The results of real-life landfill fire images verification are presented in Figure 11.



a)



b)

Figure 9: Confusion matrix in numerical (a) and in percentage (b) representations.

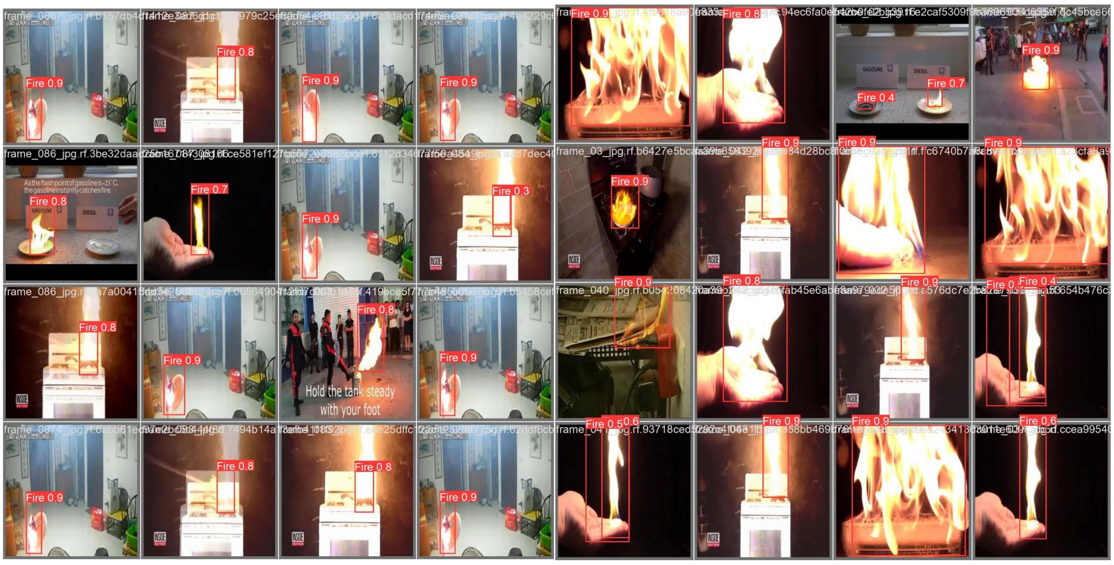


Figure 10: The results of images from Roboflow dataset verification in which the neural network detected smoke and fire.

The errors of computer vision algorithms are characterized by such parameters as Precision, Accuracy, Recall, F1 score.

Precision shows how many of the positive predictions turned out to be correct. The average precision value for our case was calculated by the formula 1.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) = 0.93707, \quad (1)$$

TP refers to the count of correctly classified positive examples, while TN denotes the count of correctly classified negative examples.

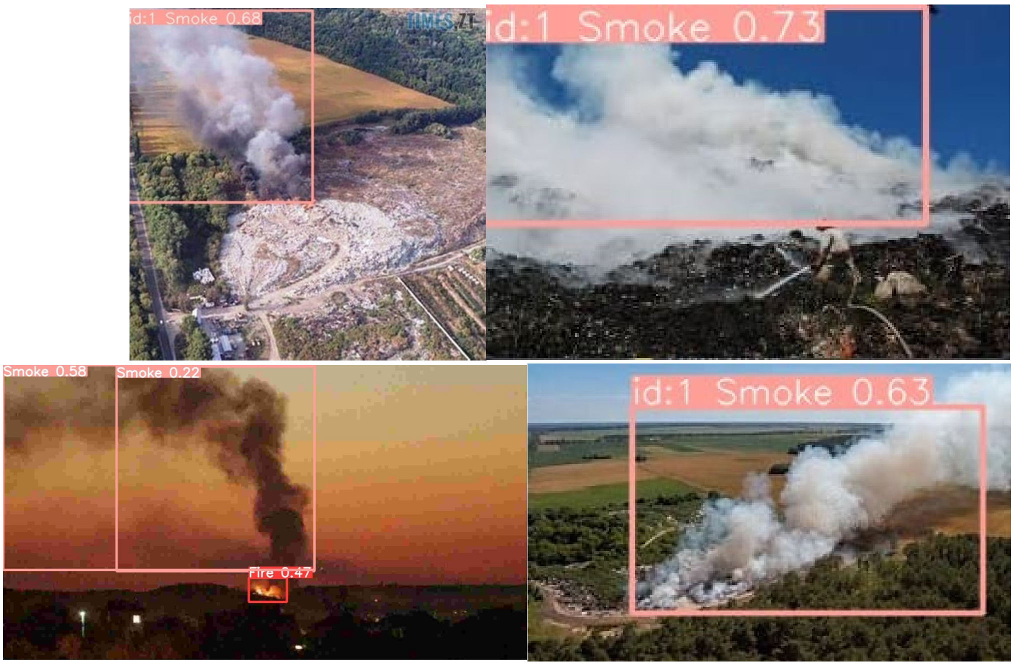


Figure 11: The results of real-life landfill fire images verification.

Recall represents the ratio of positive cases correctly identified by the model. The average recall value for our case was calculated by the formula 2.

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}) = 0.9061, \quad (2)$$

where TP is the number of correctly classified positive examples; TN is the number of correctly classified negative examples.

F1 score is a metric for measuring model performance in classification tasks. It combines precision and response into one metric to provide a balanced assessment of model accuracy. F1 score for our case was calculated by the formula 3:

$$\text{F1} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) = 0{,}9213. \quad (3)$$

6. Conclusions

Therefore, in the course of work on the problem of early landfill fire detection using external surveillance cameras, it was decided to develop a method of early detection of landfill fires using YOLOv8 neural network model.

Also, an experiment on YOLOv8-s training was conducted using Roboflow dataset. The results of the experiment were measured by such metrics as precision, recall and F1 score. The average precision value that was obtained is 0,93707 is quite high, meaning that when the model predicts an object, it is correct 93.7% of the time. This indicates that the model has a low false positive rate and is good at avoiding incorrect predictions. The model is effective at identifying true positives among the positive predictions it makes. The model has a high recall (0,9061), meaning it correctly identifies 90.6% of all actual objects. This indicates that the model has a relatively low false negative rate and is good at finding most of the actual objects present in the dataset. The model is effective at capturing the majority of true objects in the data. The F1 score, which is the harmonic mean of precision and recall, is 0.9213. This value is high, indicating a good balance between precision and recall. The model maintains a good trade-off between precision and recall, making it robust for the task at hand. The high precision and recall values, along with a high F1 score, suggest that the neural network model is performing well and is balanced in terms of making accurate predictions (high precision) and capturing most of the relevant objects (high recall). The metrics indicate that the model has been trained effectively on the given dataset. It is capable of making reliable and comprehensive detections or classifications. Overall, these metrics suggest that the model is highly accurate and has been trained successfully, making it a strong candidate for deployment in applications where high precision and recall are critical.

The future efforts of the authors will focus on the development of the information system for early landfill fire detection based on the proposed in this work method.

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