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Use of artificial intelligence and machine learning for automated detection of methane emissions on satellite images

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Abstract. The aim of this study was to analyse modern machine learning methods and their integration into the processing of satellite data for the automated detection of methane emission sources. The research examined such methods as convolutional neural networks (CNN), support vector machines (SVM), random forest (RF), and k-nearest neighbours (KNN). The main findings demonstrated the efficiency of CNNs in the automated analysis of satellite images, particularly their ability to detect spatial patterns characteristic of methane emission sources with high accuracy and resilience to noise. It was established that the implementation of this technology for monitoring in Azerbaijan confirmed its capability to promptly identify anthropogenic threats based on satellite imagery. Meanwhile, the SVM method, implemented in Python, achieved a classification result with a 90% probability in favour of methane emission presence. At the same time, the R-based programme successfully classified images into the categories "methane emissions" and "no methane emissions", effectively enabling the localisation of emission sources. The random forest method also proved effective in identifying methane sources using spectral characteristics, vegetation indices, and temperature data from satellite images. The R programme displayed the geographic distribution of methane sources, while the Python-based code validated the method's effectiveness by processing an image of the city of Baku, identifying potential methane sources even at low concentrations. In turn, the KNN method showed potential in classifying pixels by spatial and spectral features, allowing for rapid detection of hazardous zones in new satellite images. The obtained results affirm the feasibility of integrating machine learning methods into satellite monitoring systems to ensure accurate, prompt, and automated detection of methane emission sources, which is a significant step towards enhancing environmental safety and effective natural resource management in Azerbaijan and beyond

Keywords: convolutional neural network; support vector machine; random forest; k-nearest neighbours' algorithm; implementation in Python and R; satellite monitoring

Introduction

Monitoring environmental threats, particularly methane emissions, is critically important in the context of sustainable development and environmental protection. One of the key tools for conducting such monitoring is satellite imagery, which provides detailed information on the state of the environment across vast areas. The use of machine learning (ML) methods, a component of artificial intelligence (AI), enables the automation of the analysis of such images, ensuring high accuracy in detecting potential methane emission sources. These methods allow computers to perform tasks that typically require human intelligence, such as pattern recognition, decision-making, and prediction. However, despite considerable progress in this field, gaps remain in the utilisation of satellite imagery for identifying methane sources, which necessitates the integration of advanced ML methods for accurate and timely data analysis. The research problem lies in addressing these gaps and improving the processes of automated methane emission source detection using ML methods.

For instance, H. Mammadli & T. Murtuzov (2024) investigated the use of AI to enhance geological mapping, particularly the identification of geological structures on aerial and satellite images. The authors highlighted the potential of AI in analysing geological data and generating

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more accurate and detailed geological maps. S. Ibrahimova & M. Bağırzadə (2024) analysed the development of the digital economy and the implementation of digital technologies in the oil and gas industry, particularly the use of AI for process automation. They noted that the deployment of intelligent systems, such as smart wells and unmanned extraction technologies, is crucial for increasing efficiency and automation in the oil and gas sector. In addition, R. Ismayilov & Y. Mustafayev (2024) examined modern technologies for detecting leaks in gas distribution networks, particularly methane, with emphasis on their environmental, economic, and safety implications. The authors reviewed the use of acoustic sensors, infrared thermography, and drones for accurate and timely leak detection and highlighted the prospects for AI and ML integration to enhance monitoring systems.

G. Schillaci *et al.* (2024) analysed current computer vision and AI methods for monitoring and quantifying methane emissions using satellite imagery. They emphasised the necessity of applying AI for the accurate analysis of remote sensing data and addressing the lack of ground truth data. On the other hand, A.K. Koshariya *et al.* (2025) demonstrated the effectiveness of AI and ML methods, particularly CNNs, and stressed the role of satellite images, hyperspectral data, and cloud technologies in integrating AI for early monitoring. The study by H. Bi & S. Neethirajan (2024) showed the effectiveness of using Sentinel-5P satellite data in combination with ML methods for monitoring and forecasting industrial methane emissions, with long short-term memory (LSTM) models enabling precise tracking of emission dynamics and seasonal variations. Moreover, A. Karim *et al.* (2024) presented the application of neuromorphic computing (NC) and spiking neural networks (SNN) to detect point sources of methane emissions using hyperspectral images processed directly onboard resource-limited CubeSats, allowing for real-time, energy-efficient monitoring.

Furthermore, S. Sloan *et al.* (2024) demonstrated the effectiveness of deep learning methods based on CNNs, particularly UNet and ResNet models, for automated object detection in satellite images. This supports the relevance of such architectures in the automated analysis of satellite data, which can be adapted for detecting methane emission sources with high accuracy and scalability. The study by B.J. Schuit *et al.* (2023) involved a two-stage ML-based approach using CNNs to detect methane plumes in data from the TROPOspheric Monitoring Instrument (TROPOMI), as well as SVMs to filter out artefacts. The system detected 2,974 plumes in 2021, originating from landfills, urban areas, oil and gas infrastructure, and coal mines, demonstrating the high efficiency of automated satellite monitoring of methane super-emitters. Additionally, B. Rouet-Leduc & C. Hulbert (2024) showed that deep learning enables the detection of methane sources on Sentinel-2 images with high spatial and temporal resolution, identifying plumes as small as 0.01 km^2, marking a significant improvement over existing method.

While the reviewed studies focused on general approaches to methane detection, there remains a need to demonstrate the practical integration of various ML methods for satellite monitoring at the regional level. In this study, the use of CNN, SVM, RF, and KNN methods was implemented for the automated detection of methane emission sources based on satellite imagery. The research objectives included comparing the effectiveness of these methods and demonstrating their application for identifying methane emissions in Azerbaijan and other regions.

Materials and Methods

The study analysed the application of ML methods for classifying satellite images and detecting methane emission sources, specifically CNN, SVM, RF, and KNN. The CNN method was examined by schematically visualising a network architecture adapted for satellite image processing, and its main advantages and limitations in this context were identified. The second method, SVM, was implemented using a Python script developed in Visual Studio Code. This script imported essential libraries, such as sklearn for model construction and skimage for feature extraction. The methane-related image was converted to greyscale, and features were extracted using the histogram of oriented gradients (HOG) method. The model was trained on synthetic data that classified images according to the presence (1) or absence (0) of methane. A demonstration of the classification used an image of the Diamond Gas Rose tanker, which released methane while docked at the Cameron LNG (Liquefied Natural Gas) terminal in Louisiana in 2021 (Goddard, 2024). The image was acquired using satellite monitoring (Planet) and plume data from the Global Airborne Observatory via the Carbon Mapper project.

The third method was RF, implemented with R in the RStudio environment. The code included stringr and dplyr libraries to extract coordinates from image file names. These coordinates were used to construct a geographical map visualising the distribution of methane sources across the United States of America (USA). The choice of the USA was based on the high concentration of energy infrastructure facilities, which are potential sources of methane emissions. Additionally, the country actively publishes open satellite data, making it a convenient region for testing spatial analysis algorithms. The dataset comprised 7,066 aerial images, including 149 images of oil refineries and 6,917 negative images depicting similar objects and landscapes surrounding these facilities (Mexwell, 2023). The dataset was sourced from the Kaggle platform, which hosted imagery collected through the National Agriculture Imagery Program (NAIP) in the USA from 2015 to 2019. For KNN, a schematic visualisation illustrated the method's operating principle, along with an outline of its strengths and weaknesses. Furthermore, for each method, a specific example was provided to demonstrate its application in detecting methane emissions in satellite images.

The practical implementation of the described ML methods in satellite monitoring of Azerbaijan was also considered. To this end, the Earth Observing System (EOS) LandViewer online platform was demonstrated for viewing satellite imagery from the country's territory (EOS Land Viewer, n.d.). To analyse CNN integration into the methane source detection process in Azerbaijani satellite imagery, a step-by-step plan was proposed, including image pre-processing, feature extraction, CNN model construction and training, and result visualisation. For SVM, an R-based program was developed using 2023 data on methane emissions in Azerbaijan (Conway, 2024). The data included quantitative emissions by source type, such as "Offshore oil – Vented" (165), and "Offshore gas – Fugitive" (29). The program loaded and processed the data, classified the sources into high and low emission categories based on a defined threshold, constructed a linear-kernel SVM model, and visualised classification results with a plot displaying actual and predicted categories for each source.

To demonstrate the RF (Random Forest) method, a Python script was created using a satellite image of Baku, Azerbaijan (Baku Satellite image..., 2021). The selection of this location was due to Azerbaijan's status as a key oil-producing region in the Caspian area, with Baku, the capital and an industrial hub, having a high concentration of oil and gas infrastructure. The image was resized for processing efficiency and converted into a Red, Green, Blue (RGB) pixel matrix. The program used a synthetic dataset, and pixels were labelled as containing or not containing methane. The output image visualised predicted methane-emitting areas using red pixels. Additionally, a schematic was presented to show the integration principle of KNN into satellite monitoring. A step-by-step description of the main stages was provided, accompanied by a Strengths, Weaknesses, Opportunities, Threats (SWOT) analysis assessing the method's effectiveness using real satellite data.

Results

Analysis of machine learning methods for methane detection

The application of ML methods in the analysis of satellite imagery significantly enhances the accuracy and automation of detecting methane emission sources. One of the most commonly used approaches is CNN, which is particularly effective for image classification and segmentation tasks. CNN works by automatically extracting spatial features from input images using convolutional filters, enabling the detection of characteristic patterns linked to potential emission sources. A typical CNN architecture for processing satellite imagery includes a sequence of convolutional layers, activation layers such as the rectified linear unit (ReLU), pooling layers (max pooling), and fully connected layers for final decision-making (Fig. 1).

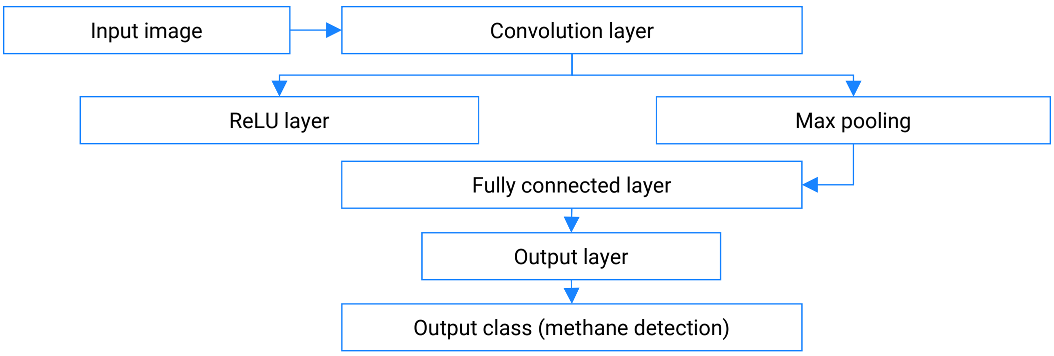

Figure 1. CNN architecture for processing satellite imagery

Source: compiled by the author

In essence, an image undergoes several processing stages–from filtering basic features and activating more complex patterns to reducing dimensionality and aggregating features for final classification of methane sources. However, despite the high effectiveness of this approach, it has both advantages and limitations. To better understand the potential of CNN in environmental monitoring tasks, a SWOT analysis of this technology was conducted (Table 1).

Table 1. SWOT analysis of using CNN for methane emission detection in satellite imagery

Strengths	**Weaknesses**
High classification accuracy of objects in images	Requires large volumes of labelled training data
Robustness to noise in images	High computational load
Automation of satellite image analysis process	Necessity for careful model architecture tuning
Ability to detect complex spatial patterns	Potential inefficiency in regions with atypical landscapes
Opportunities	**Threats**
Scalability to other emission types (e.g., carbon dioxide)	Dependence on the quality and frequency of satellite image updates

Table 1. Continued

Opportunities	Threats
Integration with other ML methods or GIS for comprehensive models	Limited access to high-resolution data
Potential for real-time response	Risks of overgeneralisation or false positives
Usability in global climate monitoring initiatives	Ethical and legal concerns over satellite data usage

Source: compiled by the author

Thus, the use of CNNs in the analysis of satellite images is one of the most effective approaches for the automated detection of methane emission sources. This method ensures high accuracy due to the model's ability to extract and interpret spatial features characteristic of potential emission sources. CNNs make it possible to process large volumes of images with minimal human intervention; however, they require substantial computational resources and high-quality training data.

Another effective method for detecting methane emissions is the SVM algorithm. This is a powerful classification tool that operates on the principle of maximising the margin between different classes. In the context of satellite imagery, SVMs can be applied to classify various types of surfaces or objects based on their features, such as texture, colour, contours, or other spatial characteristics, enabling the identification of potential methane sources, such as oil or gas wells. The SVM operates by identifying a hyperplane that best separates the data into two classes. In the case of methane detection, these may be two classes: methane present and methane absent. Figure 2 shows an example of a satellite image processed using the SVM method, where classification was carried out based on spatial features, resulting in a 90% probability in favour of the presence of methane.

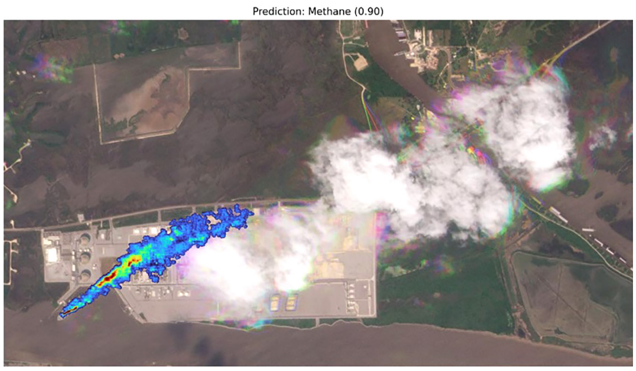

Figure 2. Result of satellite image classification using the SVM method
Source: compiled by the author based on L. Goddard (2024)

This level of probability indicates the model's high confidence in classifying the image as belonging to the methane class, which may point to a potential emission source, particularly of anthropogenic origin. Importantly, SVM employs kernel functions, which allow it to handle non-linearly separable data – a common scenario in satellite image analysis, where features may be intricately interrelated. Figure 3 presents a Python code snippet demonstrating the implementation of satellite image classification using the SVM method.

```
main.py > ...
from sklearn import svm
from skimage.feature import hog
from skimage import io, color
import matplotlib.pyplot as plt
import numpy as np

image_path = '58d54285-0634-40b1-ad4e-223803b3603c_1593x878.png'
image = io.imread(image_path)

if image.shape[2] == 4:
    image_rgb = image[:, :, :3]
else:
    image_rgb = image

image_gray = color.rgb2gray(image_rgb)

features, hog_image = hog(image_gray,
                          orientations=8,
                          pixels_per_cell=(16, 16),
                          cells_per_block=(1, 1),
                          visualize=True,
                          feature_vector=True)
```

Figure 3. Code snippet for satellite image classification using the SVM method
Source: compiled by the author

The presented example demonstrates the practical effectiveness of using SVM in the analysis of satellite images for environmental monitoring tasks. Due to the model's ability to accurately classify images based on emission indicators, it can be successfully integrated into an automated methane detection system, particularly in regions with intensive oil and gas activity. Another method for identifying methane sources is the RF algorithm. This is an ensemble algorithm based on the aggregation of a large number of decision trees, which work collectively to achieve more accurate classification. In the case of satellite image processing, RF allows the incorporation of a large number of input features (spectral characteristics, vegetation indices, temperature indicators, albedo) to identify potential zones of methane concentration. The method works by constructing several decision trees on random subsets of the data, after which each tree votes for a particular class, and the final decision is made based on the majority vote. This approach reduces the risk of overfitting, which is especially important when working with heterogeneous satellite imagery. As an example, Figure 4 shows an image illustrating the geospatial distribution of methane sources across the United States, obtained using the RF method to identify zones of methane concentration based on satellite data.

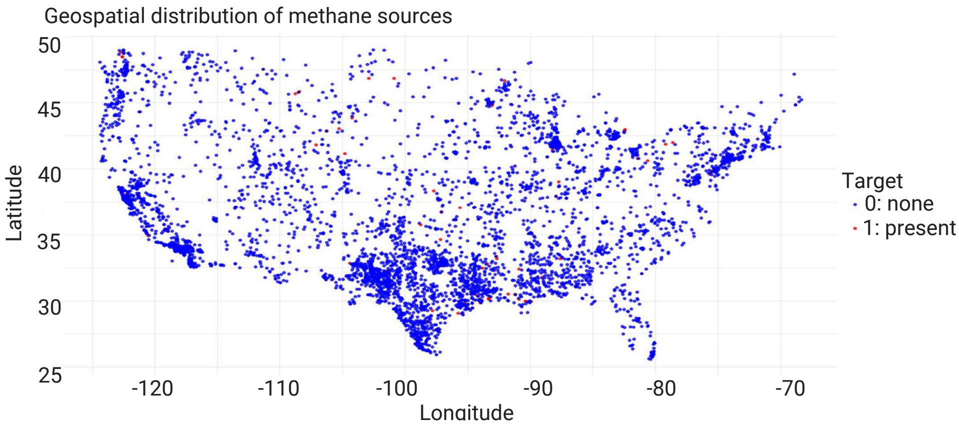

Figure 4. Geospatial distribution of methane sources in the United States
Source: compiled by the author based on Mexwell (2023)

This image is a point-based geographic map showing the distribution of methane sources across the United States. The X-axis indicates longitude, and the Y-axis latitude, enabling clear visualisation of data point locations. Each point corresponds to an image, where the colour of the point indicates the presence or absence of a methane source: blue points indicate no methane, while red points indicate presence. This plot makes it possible to identify potential geographic patterns in the distribution of methane sources. In particular, a higher concentration of emissions is observed in the southern regions of the United States compared to the northern ones, which may be due to greater industrial density, the presence of oil and gas infrastructure, and more intensive agricultural activity. A trend towards an increased number of emission sources along the coasts is also noticeable, potentially linked to the location of ports and industrial zones. For data processing and visualisation of the geographic distribution of methane sources, an R programme was used, which extracts coordinates from files and generates a point map based on these coordinates and the values of the target variable. A code snippet is shown in Figure 5.

```
> # Check that coordinates have been extracted correctly
> head(train_data)
                                                Image_Path Target      lat
1  images/image_30.48899512430464_-91.18319993235049_1.png      1 30.48900
2 images/image_29.877516654315535_-93.99023132821317_1.png      1 29.87752
3 images/image_40.90957391835373_-108.43975358129246_0.png      0 40.90957
4 images/image_31.462110423123338_-95.30886081159305_0.png      0 31.46211
5  images/image_33.94681008871147_-118.1700853494495_1.png      1 33.94681
6  images/image_34.63750604849117_-97.16573237151611_1.png      1 34.63751
        lon
1  -91.18320
2  -93.99023
3 -108.43975
4  -95.30886
5 -118.17009
6  -97.16573
>
> # Create a geographical map
> ggplot(train_data, aes(x = lon, y = lat, color = factor(Target))) +
+     geom_point(alpha = 0.6, size = 2) +
+     labs(title = "Geospatial Distribution of Methane Sources",
+          x = "Longitude", y = "Latitude", color = "Target") +
+     scale_color_manual(values = c("blue", "red"), labels = c("0: No", "1: Yes")) +
+     theme_minimal()
```

Figure 5. Code snippet for building a geographic map of methane sources using the RF method
Source: compiled by the author

The use of the RF method for satellite data containing information on methane presence enables the automation of the detection process of methane sources based on geospatial imagery. This approach is significant in the current context as it facilitates the development of efficient algorithms for the automated monitoring of methane emissions across vast areas. RF is capable of processing complex and heterogeneous satellite images by analysing numerous spectral features and other indicators, thereby improving the accuracy of identifying potential methane sources.

On the other hand, the K-Nearest Neighbours (KNN) method is also effective when working with satellite imagery (Figure 6). This method is simple and intuitive, yet powerful for classification tasks. The principle of KNN involves searching for the nearest neighbours from the training dataset for each new object (pixel in the image). The object's class is determined by the majority class among its neighbours. The choice of the number of neighbours (*k*) is essential for the method's effectiveness.

The diagram illustrates the step-by-step classification process of a satellite image pixel using the KNN method. It involves extracting spatial and spectral features of a pixel, calculating distances to training samples, selecting the *k* nearest neighbours, and determining the class by majority vote. Overall, KNN performs well in processing satellite images as it can effectively analyse spatial features, such as pixel values or spectral indices, and classify based on these features. One of the advantages of this method is its simplicity and the lack of a need to train a model, making it fast to deploy. However, KNN has certain limitations, such as high computational complexity for large datasets and sensitivity to the choice of the parameter *k*. For effective methane detection using KNN, it is crucial to carefully tune this parameter to ensure high accuracy and low error rates.

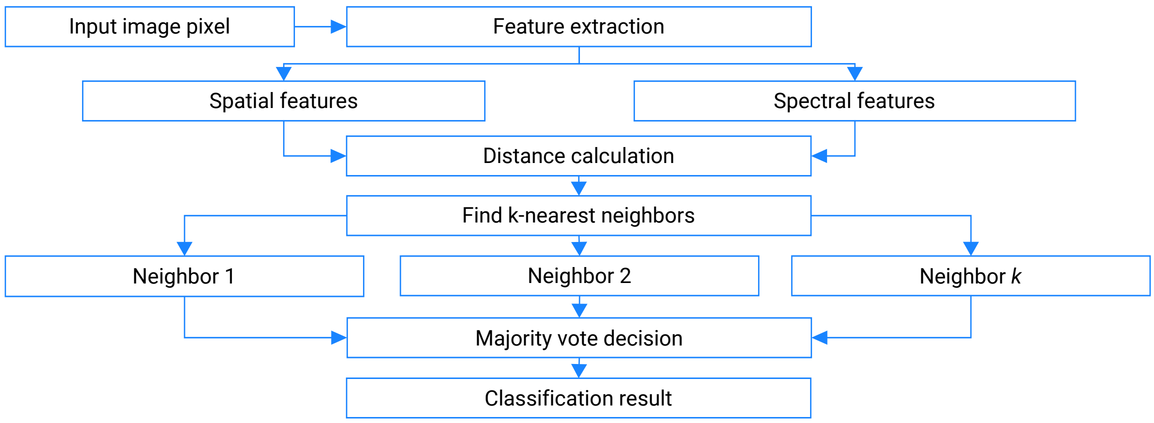

Figure 6. KNN method scheme for satellite image classification

Source: compiled by the author

Thus, in the context of automated methane emission source detection from satellite imagery, the considered ML methods can be applied to various aspects of data processing. For instance, CNNs are effective for segmenting satellite images to isolate areas with suspicious patterns that may correspond to methane sources. The SVM method is suitable for classifying areas based on spectral features, where the model estimates the likelihood of methane presence in individual pixels or image segments. The RF algorithm can be employed to integrate a wide range of satellite indicators, such as Normalised Difference Vegetation Index (NDVI), albedo, or temperature data, to build a probability map of emission sources. Additionally, the KNN method enables rapid classification of new image areas by comparing textural or spectral characteristics with training examples of methane sources. Therefore, each of these methods can be purposefully integrated into a satellite monitoring system to address specific tasks, and their combined use can enhance the accuracy, flexibility, and efficiency of analysis, forming a reliable foundation for the development of automated environmental monitoring systems.

Implementation of ML methods in satellite monitoring in Azerbaijan

Given the significant resources of Azerbaijan's oil and gas industry, detecting methane emissions is a key task for environmental monitoring. Automating this process through ML methods and satellite imagery substantially increases monitoring efficiency and reduces the costs associated with traditional methods. The use of satellite images enables coverage of vast areas, allowing for real-time or historical tracking of methane sources. The application of methods such as CNN, SVM, RF, and KNN to images from various satellite systems allows for automatic identification of potential methane sources at oil and gas fields, refineries, and other infrastructure facilities.

It is worth noting that Azerbaijan is one of the leading oil and gas exporters in the South Caucasus region, which results in a high environmental burden due to intensive resource exploitation. The country's geopolitical importance as a transit hub for energy carriers to Europe and Asia increases the demand for environmental responsibility and transparency in extraction operations. At the same time, the complex terrain, large spatial scale of industrial facilities, and limited access to certain areas render traditional monitoring methods ineffective. In this context, the application of ML methods based on satellite imagery is highly relevant, as it ensures continuous monitoring of methane emissions, timely detection of irregularities, and improved environmental safety in the oil and gas sector.

The use of satellite images such as those from Sentinel-2 allows for regular monitoring of large areas, which is critical for identifying potential sources of methane emissions. For instance, EOS LandViewer provides access to satellite imagery, including Sentinel-2 data, for the territory of Azerbaijan (Fig. 7). This is an online platform that enables viewing, analysing, and downloading satellite images from various sources. It supports preprocessing tools, including the selection of spectral bands, indices (e.g., NDVI), and filtering by date.

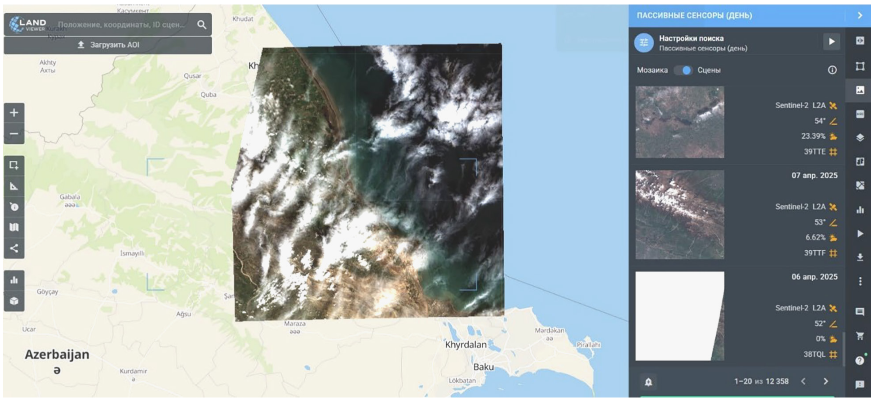

Figure 7. Use of EOS LandViewer for viewing satellite images of Azerbaijan
Source: compiled by the author based on EOS Land Viewer (n.d.)

Thus, the use of EOS LandViewer may be helpful for preliminary analysis and identification of potential methane emission zones in Azerbaijan, which can then be examined in more detail using specialised data, such as infrared or hyperspectral images, and ML methods can be applied for the automated detection and classification of emission sources. In this regard, CNNs may be effectively applied to Sentinel-2 images, which offer sufficient spatial resolution, as well as to hyperspectral imagery (Table 2). With the help of EOS LandViewer or similar platforms, it is possible to prepare training samples for CNNs by labelling areas near known fields, such as the Sangachal Terminal or the Naftalan oil field, as potential emission sources. This would enable the creation of a specialised model for the automatic detection of similar structures in other images.

Table 2. Step-by-step integration of CNN in the satellite monitoring process for detecting methane sources in Azerbaijan

Step	Description	Purpose
1. Data preparation	Use platforms such as EOS LandViewer to download Sentinel-2 and other types of imagery (hyperspectral or infrared)	Collect data necessary for model training
2. Image preprocessing	Select spectral bands, filter by date, compute indices (e.g., NDVI) to improve detection accuracy	Prepare images for further analysis
3. Data labelling	Identify and label areas near known methane sources, such as the Sangachal Terminal or Naftalan oil field	Create training datasets for the CNN model
4. CNN model development and training	Use labelled images to train the CNN. Develop a deep neural network for automatic methane source detection	Train the model to detect potential methane emission zones
5. Model evaluation and validation	Test model performance on test images. Assess accuracy and sensitivity	Determine model precision and reliability
6. Application of the model to new imagery	Identification of potential methane sources in new satellite imagery of Azerbaijan	Application of the model to real data for methane emissions monitoring

Source: compiled by the author

The implementation of CNN in satellite monitoring of Azerbaijan can be effectively realised through automated detection of methane sources based on satellite image processing. By using platforms for data downloading and preprocessing – particularly through the selection of spectral bands and indices – high-quality training datasets can be prepared for CNN training. Once developed and trained, the model can detect potential methane sources, automating the monitoring process over vast areas, including oil and gas facilities. This enables prompt identification of emission sites, minimising the need for manual intervention and enhancing the efficiency of real-time environmental monitoring.

On the other hand, the use of SVM allows for the classification of images into categories such as "methane emissions" and "no methane emissions," thereby enabling effective tracking and localisation of potential emission sources. Due to SVM's capability to operate with high-dimensional data, this method is particularly valuable in processing satellite images containing a large number of pixels and spectral bands. Once trained on relevant data, the model can be used for automatic classification of new images, ensuring timely detection of methane emissions across extensive areas such as oil and gas fields in Azerbaijan (Fig. 8).

Figure 8. Classification of methane emissions using SVM
Source: compiled by the author based on T.J. Conway (2024)

This figure illustrates the output of an R-based programme that classifies methane emissions into "Low" and "High" categories using an SVM model, based on methane emission data in Azerbaijan for 2023. The X-axis represents the volume of methane emissions by source, while the Y-axis shows the actual ("Category") and predicted ("Predicted") emission categories. Red points represent the "Low" category and are concentrated in the range of low emission values, whereas turquoise points correspond to the "High" category with higher emission values. The predicted SVM categories generally reflect the actual categories well, demonstrating the model's effectiveness in classifying methane emissions in Azerbaijan. SVM is effectively integrated into Azerbaijan's satellite monitoring system as a tool for automated satellite image processing aimed at detecting methane sources. Owing to its ability to handle high-dimensional spectral data, SVM allows for the classification of image segments by emission indicators, making it useful for rapid analysis of large territories and identification of potentially hazardous zones without manual processing.

In turn, in the context of Azerbaijan's satellite monitoring, RF can also be utilised for image classification and detection of methane sources across large areas. Thanks to its ability to handle a large number of input variables and provide feature importance assessments, RF is well-suited for processing complex satellite imagery that contains numerous spectral bands and pixel information. Following the preliminary stage – which includes downloading and preprocessing images (e.g., date filtering, spectral band selection) – RF should be applied to classify pixels into categories corresponding to methane emissions. Due to its flexibility, RF allows for the identification of even minimal methane emissions in images, which can be particularly valuable for monitoring detected zones where methane is released in very low concentrations (Fig. 9).

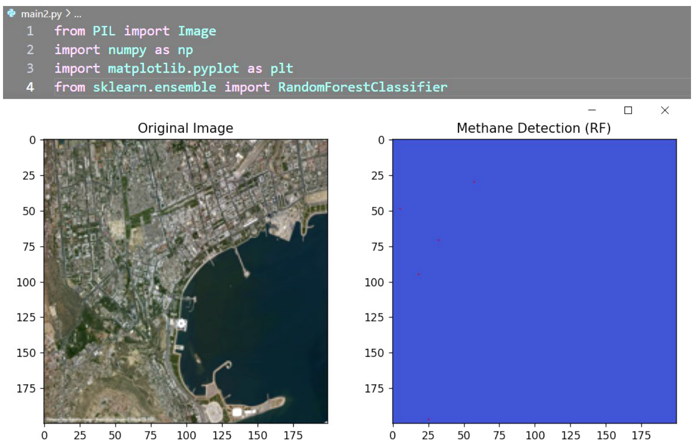

Figure 9. Methane detection using the RF method
Source: compiled by the author based on Baku Satellite image from Pleiades Neo (2021)

The results show the output of a Python-based programme that processes a satellite image of Baku, highlighting the pixels where the RF algorithm detected potential methane sources. The comparison of these points with real-world objects on the map shows that potential emissions are mainly localised on land – in industrial areas, near oil and gas fields, processing facilities, and transport infrastructure. At the same time, no emission points were detected in the marine area, which may indicate either a lower level of emissions in that environment or the complexity of their detection in aquatic environments using satellite imagery. However, the detected methane areas are very small, indicating a minimal presence of methane in the image. This result clearly demonstrates how the RF method can help detect even weakly expressed methane emissions, which is important for real-time environmental monitoring. In other words, RF is a highly effective tool for satellite image analysis and detection of minimal methane emissions, making it useful for Azerbaijan's environmental monitoring system, where such small sources of methane may significantly impact the region's overall environmental condition.

As for the KNN method, it can be applied to classify image regions based on signs of potential methane emissions. Despite its simplicity, this method is effective for tasks where there is a sufficient amount of labelled data describing pixel behaviour in zones with and without methane emissions. KNN operates on the principle of similarity: each new sample is classified based on the predominant category among its *k* nearest neighbours in a multi-dimensional feature space. For effective implementation of the KNN method in Azerbaijan's satellite monitoring system, Figure 10 presents a step-by-step procedure involving sequential processing of satellite data with image classification based on nearest neighbours.

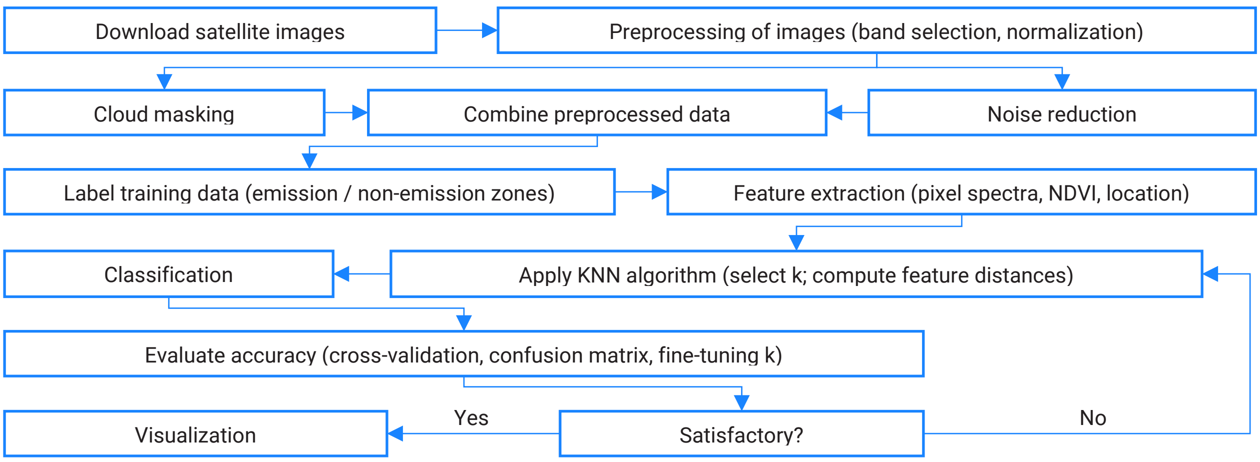

Figure 10. KNN method implementation scheme in satellite monitoring of Azerbaijan
Source: compiled by the author

The provided diagram illustrates the full cycle of applying the KNN method – from obtaining satellite images and their preliminary processing to classification and accuracy assessment of the results, with the possibility of returning to the model parameter tuning stage to improve the effectiveness of detecting methane emission sources. Within the satellite monitoring of Azerbaijan's territory, the KNN method can be used for automated classification of image areas based on spectral features characteristic of methane emission sources. In particular, pre-processed satellite data are transformed into a set of numerical vectors that describe pixels by intensity in relevant spectral bands. Using a labelled training set (presence or absence of emissions), the KNN model enables automatic identification of similar areas in new images, ensuring the rapid detection of potentially hazardous zones. This approach is integrated into the overall process of satellite analytics, providing an effective tool for spatial control of emissions in the country's oil and gas regions.

Thus, the introduction of ML methods and AI tools into Azerbaijan's satellite monitoring opens new opportunities for effective and automated detection of methane emission sources. The use of CNN, SVM, RF, and KNN, in combination with satellite images, particularly Sentinel-2, enables coverage of large areas, improves classification accuracy, and ensures timely responses to environmental threats. Platforms such as EOS LandViewer allow not only the acquisition of the necessary images but also preliminary processing and labelling of data for further analysis. The results obtained confirm the effectiveness of these approaches in identifying both major and minor methane sources at oil and gas facilities, contributing to improved environmental monitoring quality and reducing the need for costly field studies.

Discussion

The results of this study, focused on the automated detection of methane emission sources using satellite imagery and ML methods, deepen and specify the topic outlined in the work by S. Kumar *et al.* (2023). Their study provides a general overview of the application of AI and ML methods to satellite data for managing natural resources, climate change, and urban development. However, it is more general in nature and targets a wide range of remote sensing tasks. In contrast, the current study offers a practical focus, demonstrating the specific implementation of ML methods for methane detection with software examples and result visualisations.

The application of CNN in this study demonstrated high efficiency in the task of automated detection of methane emission sources on satellite images. Due to the model's ability to extract distinctive spatial features, CNN enables accurate identification of potentially hazardous areas, particularly near oil and gas facilities. Similar results were obtained in the study by A.V. Sable *et al.* (2024), where CNN was used for image classification. The author emphasised the importance of combining features from different levels of the model to improve accuracy, which aligns with current observations regarding the need for careful CNN architecture tuning when working with satellite images.

Similarly, to the study by A. Radman *et al.* (2023), the current research analysed the use of Sentinel-2 satellite imagery. However, it focused on automated methane detection using ML methods, whereas the referenced study primarily emphasised the accuracy of quantitative methane emission estimation using deep learning models. The present results complement those of the referenced study, demonstrating a specific application of ML for monitoring environmental threats at the local level, while the other study focuses more on global monitoring and model refinement for methane emissions.

J. Bairy *et al.* (2025) applied AI and ML methods for predicting greenhouse gas emissions, using gradient boosting and deep learning algorithms to analyse emission data. In contrast, the current study focuses on the automated detection of methane emission sources based on satellite imagery. Therefore, the current findings confirm the effectiveness of ML methods in automated methane detection, particularly via satellite images, which can significantly enhance the accuracy and detail of methane emission monitoring at the local level compared to the more general prediction methods used in the referenced study.

In turn, the results of Sugeng & H. Praminiarto (2024) demonstrated the use of the SVM method for classification tasks based on simple numerical features, achieving an accuracy of 77%. In the current study, SVM was used to classify complex spatial features of satellite images containing a large number of pixels and spectral bands. Under such conditions, the model can achieve up to 90% accuracy in detecting methane emission sources. This indicates that SVM is highly effective not only in tasks with simple input features but also in high-dimensional and structurally complex data, as is typical in satellite image processing.

The conclusions of this study also align with those of H. Duan *et al.* (2023) regarding the effectiveness of the RF method for detecting methane emissions using satellite data. The authors applied RF to predict diffuse emissions from Lake Taihu based on Aqua/MODIS data, achieving an R^2 accuracy of 0.65. Similar to the current work, RF proved capable of processing a large number of satellite features and detecting methane sources, including low-intensity emissions. Therefore, both approaches confirm that RF is a reliable method for environmental monitoring due to its flexibility, high accuracy, and ability to handle heterogeneous data.

It is worth noting that in Azerbaijan, where many types of mud volcanoes exist, natural methane sources – particularly volcanic emissions – play a significant role in the total volume of greenhouse gas emissions. According to a study by T. Rashidov (2019), some volcanoes can emit large volumes of methane (up to 96,000 m^3 in a single strong eruption), exceeding the emissions from some anthropogenic sources. In this context, the application of satellite technologies and ML methods for the automated detection of methane emissions in Azerbaijan becomes particularly relevant, as it allows not only the identification of anthropogenic sources (oil and gas facilities) but also the monitoring of natural processes, such as mud volcano activity – something that was previously difficult to achieve using traditional methods due to hazardous conditions and irregular activity.

The current results demonstrated the effectiveness of ML methods – particularly CNN, SVM, RF, and KNN – for the automated detection of methane emission sources in satellite images. This is consistent with the study by P. Xu *et al.* (2024), which also analysed the use of ML and AI in image processing. However, the conducted study focused on environmental issues, such as methane emission monitoring, while the referenced work covered a broader range of applications for image processing in various scientific fields.

The study used Python to implement ML models for environmental monitoring and automated methane detection in satellite imagery, which shows some similarity to the study by O.A. Marzouk (2023), where Python was also used to model complex processes, specifically the thermodynamic calculation of methane combustion temperatures. Although the focus of the studies differs, both approaches illustrate the broad capabilities of Python as a universal tool for scientific computation and data processing in complex applied problems related to methane detection.

This study highlighted the high effectiveness of CNN for the automated detection of methane emission sources, particularly near oil and gas facilities. Similar results are presented in the work of A.M. Braik & M. Koliou (2024), where CNN, in combination with Geographic Information Systems (GIS), was employed for high-precision spatial identification of objects based on satellite images. Despite differences in the applied context, both studies confirm the effectiveness of CNN combined with geospatial analytics for the automated interpretation of satellite data.

Moreover, in this study, the KNN method was used for the automated classification of satellite images to identify methane emission sources in Azerbaijan, taking into account the spectral characteristics of pixels. In contrast, the study by A.F. Alshammari (2024) implemented KNN in Python for the classification of general data, with a focus on the technical steps of the algorithm. Both approaches demonstrate the reliability of the KNN method and the Python language; however, the present study adapts this method for satellite monitoring tasks, thereby expanding its application domain.

Overall, the obtained results encompass an analysis of the CNN, SVM, RF, and KNN methods. At the same time, the study by D.V.R. Kumar *et al.* (2025) also demonstrated high accuracy in using the SVM method for segmented image classification. However, their approach was focused on the application of K-Means for segmentation, whereas the current study applied a broader set of methods, enabling a more in-depth analysis. Thus, despite technical differences, the results of both studies are consistent in demonstrating the high efficiency of ML for satellite image classification.

In comparison with the work by Y. Xing *et al.* (2025), which applied the Multi-Attention Mechanism You Only Look Once (YOLOv9) method to detect methane emissions using high-resolution optical satellite images, the present study employed ML methods for satellite image analysis. Both approaches aim to improve the accuracy of methane source detection. However, the mentioned study uses a modified YOLOv9 with additional modules to enhance detection performance under complex background conditions. Meanwhile, the present study focuses on the application of CNN, SVM, RF, and KNN for satellite image classification, which also confirms the effectiveness of ML technologies for methane detection.

Whereas the current study used ML for classifying and analysing satellite images to detect land-based methane sources, the research by Y. Marcon *et al.* (2025) focused on measuring the characteristics of underwater methane bubbles using two consumer cameras and a neural network for automatic bubble detection. The BURST method proposed by the authors allows for accurate measurement of methane flux in underwater conditions without the use of complex equipment – the main difference from the use of satellite images for monitoring methane emissions on land in the present study. Similarly, to the research by Y. Chen *et al.* (2020), the current study employs a CNN-based approach to detect important objects in images. However, the referenced study focuses on detecting satellite components using an optimised Region-based CNN (R-CNN) architecture, whereas the present research targets the detection of methane emissions in satellite images, applying CNN, SVM, RF, and KNN methods for classification. Thus, both approaches demonstrate the effectiveness of modern CNN techniques for improving object detection accuracy under challenging conditions.

In comparison with other studies, the current work focuses on the accurate classification of complex spatial features in satellite images, enabling high detection rates of methane even in difficult conditions, such as proximity to oil and gas infrastructure or natural methane sources. The approach, which integrates various ML methods, provides detailed localisation of methane emissions, making this study more specific and practically oriented compared to other works that employ more general or global approaches.

Conclusions

In the course of analysing ML methods for detecting methane emission sources, it was found that CNNs provide high accuracy in classifying and segmenting satellite images, effectively identifying spatial patterns characteristic of methane emission sources. SVM showed strong performance in classifying satellite imagery, particularly for distinguishing areas with a high likelihood of methane emissions. The RF method proved effective for analysing spectral characteristics, vegetation indices, and temperature data, enabling accurate localisation of methane sources. Meanwhile, the KNN method showed potential for rapid pixel classification based on spatial and spectral features, although it requires improvement for more accurate detection in high-noise images.

The implementation of these methods in the satellite monitoring of Azerbaijan confirmed their capability to effectively detect methane emission sources. The use of the EOS LandViewer platform for viewing satellite images enabled the identification of potential emission points, and the application of CNNs for image processing allowed for the effective extraction of methane indicators with high accuracy. Furthermore, emission classification using SVM in the R language ensured precise categorisation of emissions, while the RF method, implemented via Python, enhanced detection accuracy through the analysis of interrelations among image parameters. The analysis of the KNN method demonstrated its effectiveness in classifying image areas based on spectral features typical of methane sources, which contributed to the prompt identification of potential emission points and improved the overall effectiveness of satellite monitoring.

A limitation of this study is the lack of access to all possible types of satellite images for certain regions, which may affect the generalisability of ML method applications. Another important limitation is the need for large volumes of training data, which requires significant computational resources. For future research, it is recommended to expand the set of images used, including data from various satellites, and to optimise the data preparation process to achieve higher accuracy. Additionally, it would be appropriate to implement deep learning methods for the automated detection of other environmental pollutants.

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Conflict of Interest

None.

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Використання штучного інтелекту та машинного навчання для автоматичного виявлення викидів метану на супутникових знімках

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Анотація. Метою цього дослідження був аналіз сучасних методів машинного навчання та їх інтеграція в обробку супутникових даних для автоматичного виявлення джерел викидів метану. У дослідженні розглянуто такі методи, як згорткові нейронні мережі (CNN), методи опорних векторів (SVM), випадковий ліс (RF) та k-найближчих сусідів (KNN). Основні результати продемонстрували ефективність CNN в автоматизованому аналізі супутникових знімків, зокрема їх здатність виявляти просторові закономірності, характерні для джерел викидів метану, з високою точністю та стійкістю до шуму. Було встановлено, що впровадження цієї технології для моніторингу в Азербайджані підтвердило її здатність оперативно виявляти антропогенні загрози на основі супутникових знімків. Тим часом метод SVM, реалізований на Python, досяг результату класифікації з 90 % ймовірністю на користь наявності викидів метану. Водночас програма на основі R успішно класифікувала зображення за категоріями «викиди метану» та «відсутність викидів метану», що ефективно дозволило локалізувати джерела викидів. Метод випадкового лісу також виявився ефективним у виявленні джерел метану за допомогою спектральних характеристик, індексів рослинності та даних про температуру із супутникових знімків. Програма R відобразила географічний розподіл джерел метану, тоді як код на основі Python підтвердив ефективність методу, обробивши зображення міста Баку, визначивши потенційні джерела метану навіть при низьких концентраціях. У свою чергу, метод KNN продемонстрував потенціал у класифікації пікселів за просторовими та спектральними ознаками, що дозволяє швидко виявляти небезпечні зони на нових супутникових знімках. Отримані результати підтвердили можливість інтеграції методів машинного навчання в системи супутникового моніторингу для забезпечення точного, оперативного та автоматизованого виявлення джерел викидів метану, що є значним кроком до підвищення екологічної безпеки та ефективного управління природними ресурсами в Азербайджані та за його межами

Ключові слова: згорткова нейронна мережа; метод опорних векторів; випадковий ліс; алгоритм *k* найближчих сусідів; реалізація на Python та R; супутниковий моніторинг