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IARIA

Detection of Gas Flares Using Satellite Imagery

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- 2014-: Director of the International Research Laboratory for Mathematical Methods for Social Network Mining at RANEPA
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Gas Flares and Oil

- The associated petroleum gas is formed during:
  - oil extraction,
  - oil transportation,
  - processing of oil.
- The gas usually disposed in flares.
- It is environmental challenge.
- It is import to monitor the gas flares.

Gas Flare Detection Problem

- Objective instrumental methods for detecting gas flares
- Assessing the volumes of gas burnt on gas flares
- Based on multi-spectral remote sensing:
  - Nighttime Earth
  - Daytime Earth
- **Output:**
  - the list of gas flares locations and flare types
  - a few thousands of locations

Gas Flares Checking

- Requires visual examination of the locations of the alleged gas flares on high-resolution daytime images.
- Automating reduces the cost of the checking and monitoring flares.
- **Our Approach:**
  - automated list verification of high-temperature anomalies.
  - it is based on the classification of daytime satellite images.
  - the classification is carried out using machine learning methods.

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Image Training Dataset

- We use satellite imagery (from the TerraServer web site) for the period 2010-2017 :
  - about 11000 images,
  - resolution of the images is within 1 m per pixel.
- The images include:
  - different types of gas flares, and
  - images without gas flares.
- Images can contain ”clouds” and ”snow cover” as natural disturbances in our classification task.

Daytime Image Examples

Examples of ”clean” upstream flare images

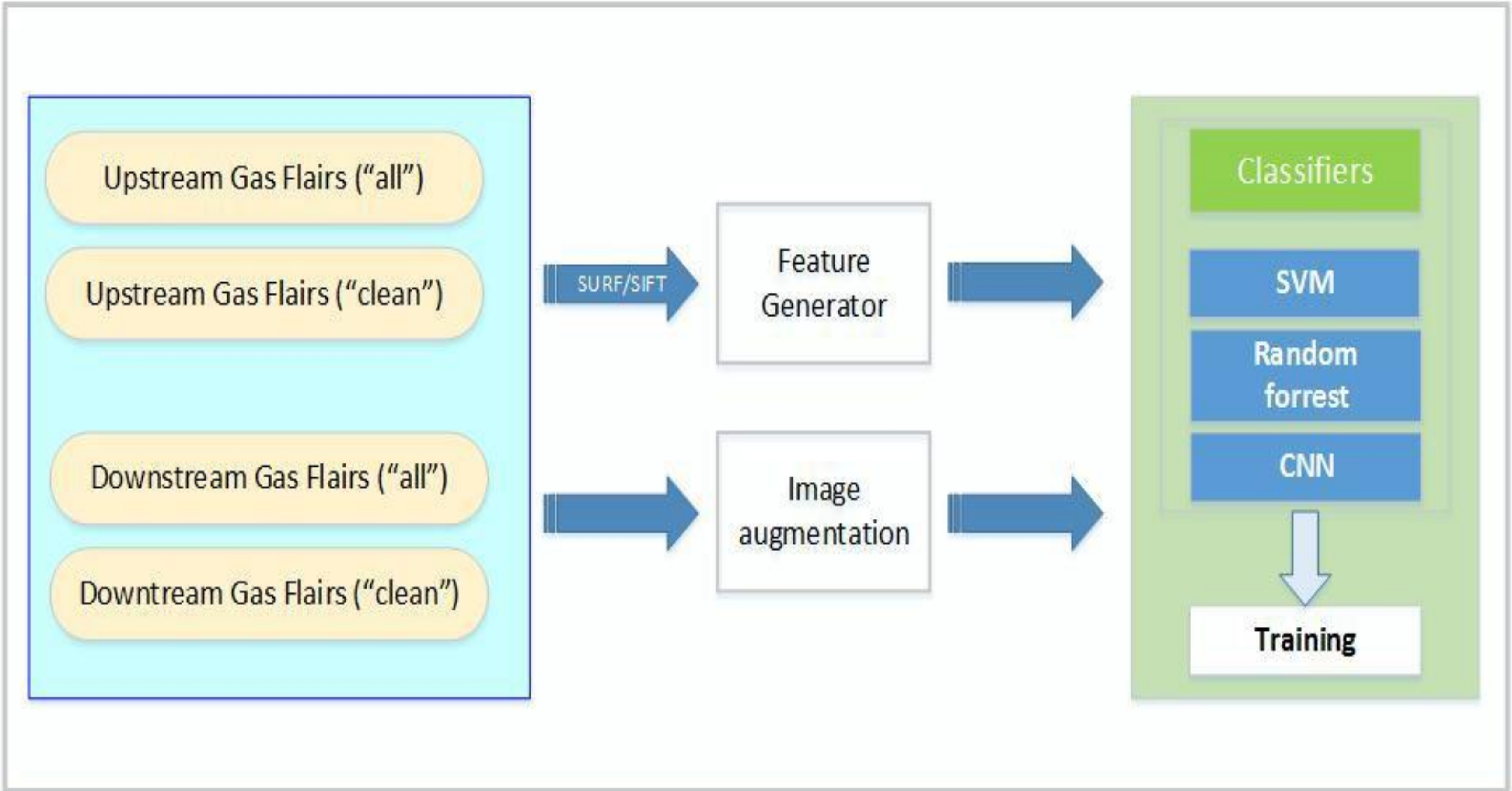
Examples of ”clean” downstream flare images

Daytime Image Examples (with clouds/snow)

Downstream flare, covered with clouds

Upstream flare, covered with snow

Stages of processing for gas flare images



Average accuracy for two classes
(upstream (or downstream), no flares)

Data	SVM	Random Forrest	CNN
Upstream "Clean"	0.81	0.79	0.75
Downstream "Clean"	0.78	0.78	0.74
Upstream "all"	0.79	0.76	0.75
Downstream "all"	0.77	0.76	0.74

Average accuracy for three classes
(upstream, downstream, and no flares)

Data	SVM	Random Forrest	CNN
Upstream,”clean” **+** Downstream, ”clean”	0.72	0.71	0.70
Upstream, ”all” **+** Down- stream, ”all”	0.70	0.70	0.68

Conclusions

- A method for checking and correcting the list of high-temperature anomalies is proposed.
- The image classification of daytime satellite gas flare images is carried out using machine learning and image processing methods.
- For different variants of datasets (”clean” (without snow and clouds); ”all” (all images)), the flare image classification is performed.
- The preliminary comparison of the classification quality for different machine learning methods (SVM, random forest, CNN is carried out.
- The following average forecast accuracy is achieved in the experiments: about 75% for the two classes and about 70% for the three classes.
- Future work concerns the improvement of the classification accuracy of the machine learning models used in the paper.

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Thank you!