INGV Istituto Nazionale di Geofisica e Vulcanologia

Session: 3.1 Calibration & Algorithms (S9)
12/May/2023, 9:00am - 10:30am

Topics: **Hot temperature events – vulcanology/fires**

Deep learning for the detection of volcanic thermal anomalies from satellite images

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Abstract ID: 150
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UNIVERSITÀ DEGLI STUDI DI PALERMO

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Motivation

- Promptly detecting the onset of a volcanic eruption is fundamental for volcano hazard monitoring;
- Satellite sensors provide thermal data over potentially hazardous, high-temperature volcanic phenomena, with relatively low cost and no risk for users;
- Traditional intensity-based approaches may fail when applied worldwide, for the lack of generalization capabilities;
- Lately, we have proposed a change of paradigm, exploiting spatial features as well as intensity, to map subtle thermal anomalies, using Deep Learning Convolutional Neural Networks (DL CNN) [1];
- Here, we propose a DL-approach to readily detect volcanic activity using images as they come from different satellite sensors;
- We use advanced learning techniques which strongly reduce training times and improve the accuracy level.

Image source: https://www.museodelletna.it/eruzioni-storiche-etnee/

[1] Corradino C., Ramsey M. S., Pailot-Bonnétat S., Harris A. J. L. and Del Negro C., *"Detection of Subtle Thermal Anomalies: Deep Learning Applied to the ASTER Global Volcano Dataset,"* in IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-15, 2023.

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Volcano selection

For representativity of the dataset, we choose volcanoes from around the world with different characteristics.

TABLE I - List of volcanoes and years with eruptive activity since 2000, sampled for the study.

Volcano	Eruptive activities in the 2000s
Cumbre Vieja	2021
Etna	2013 - 2014 -2017 - 2018 - 2019 - 2020 - 2021 - 2022
Pico do Fogo	2014 - 2015
Volcán de Fuego	2017 - 2019 - 2020 - 2021
Geldingadalir	2020 - 2021
Kilauea	2020-2021
Klyuchevskaya Sopka	2020 - 2021
Pacaya	2020 – 2021
Stromboli	2014 - 2019 - 2020 - 2021

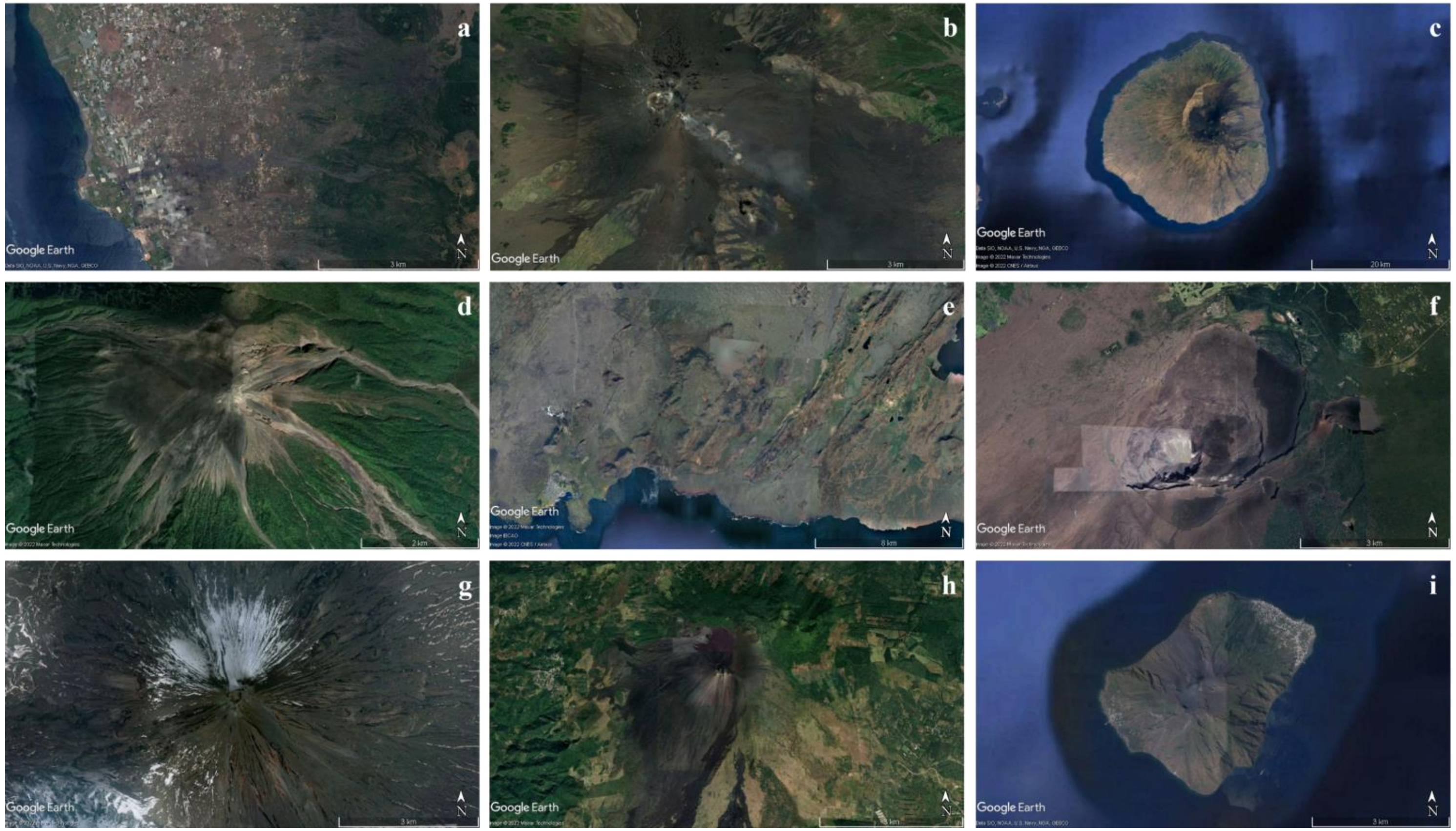

Fig. 1. Volcanoes: a) Cumbre Vieja (La Palma, Spain), b) Etna (Italy), c) Pico do Fogo (Cape Verde), d) Volcán de Fuego (Guatemala), e) Geldingadalir (Iceland), f) Kilauea (Hawaii, USA), g) Klyuchevskaya Sopka (Kamchatka, Russia), h) Pacaya (Guatemala), i) Stromboli (Italy). All the images were captured via Google Earth Pro [http://www.earth.google.com].

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Satellite sensors overview

Sentinel-2 and Landsat 8 sensors have similar range of spectral bands (visible-infrared). Either one can be used according to their availability.

TABLE II – Satellite data used

Satellite	Characteristics	Bands used
ESA **Sentinel-2 (S2)**	Launched in 2015 and 2017: Sentinel-2A (S2A) and Sentinel-2B (S2B) Revisit frequency: 10 days (one satel.), 5 days (S2A+S2B) MultiSpectral Instrument (MSI): 13 spectral bands (10 m spat. res. visible, near infrared, 20 m red edge, shortwave infrared, 60 m atmospheric bands)	Near InfraRed (NIR: B8 with 0.84 μm (S2A) / 0.83 μm (S2B)) Short-Wave InfraRed (SWIR: B11, with 1.61 μm (S2A, S2B), B12, with 2.20 μm (S2A) / 2.19 μm (S2B))
USGS&NASA **Landsat 8 (L8)**	Launched in 2013 Revisit frequency: 16 days Operational Land Imager (OLI): 9 spectral bands (30 m spat. res. visible, near infrared and shortwave infrared + 15 m spat. res. panchromatic band) Thermal InfraRed Sensor (TIRS): 2 bands (100 m spat. res.)	Near InfraRed (NIR: B5 with 0.85-0.88 μm) Short-Wave InfraRed (SWIR: B6 with 1.57-1.65 μm, B7 with 2.11-2.29 μm)

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Three-step approach

We present a satellite thermal monitoring system to automatically detect high-temperature anomalies related to active lava flows or vents, divided into three steps:

- Creation of a volcanic dataset to train the DL model, collecting representative satellite images from scenes with presence or not of thermal anomalies;
- Re-training of the Deep SqueezeNet CNN models using transfer learning approach;
- Combination of the trained models using ensemble learning approach, and application over new data.

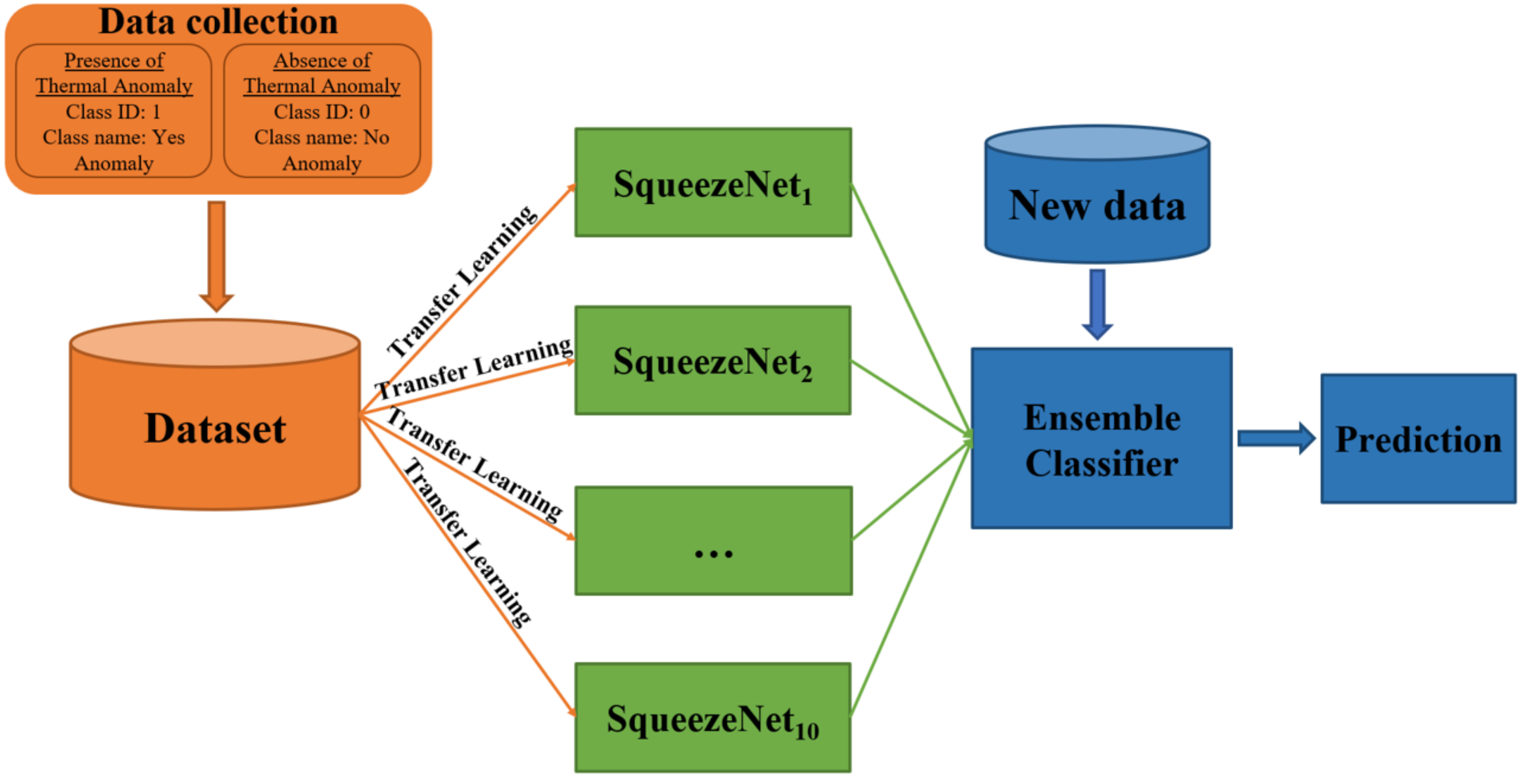

Fig. 2. Flow chart of the three-step approach

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Deep Learning approach

DL aims at replicating the way in which the human visual system detects features to automatically extract them from images without human supervision.

CNN is a DL class that uses locally connected layers to learn from input data by extracting discriminative features, generated with growing complexity over layers from input to output.

We use a SqueezeNet model, a compact and fast CNN with a good balance between training time and classification accuracy [2].

The SqueezeNet is used with the **Transfer Learning** technique, which quickly retrains a pre-trained model over a new domain (as opposed to training from scratch) [3].

We train multiple SqueezeNets and combine their outcomes in order to achieve better predictive performances than the individual models, *i.e.*, **Ensemble Classifier** [4].

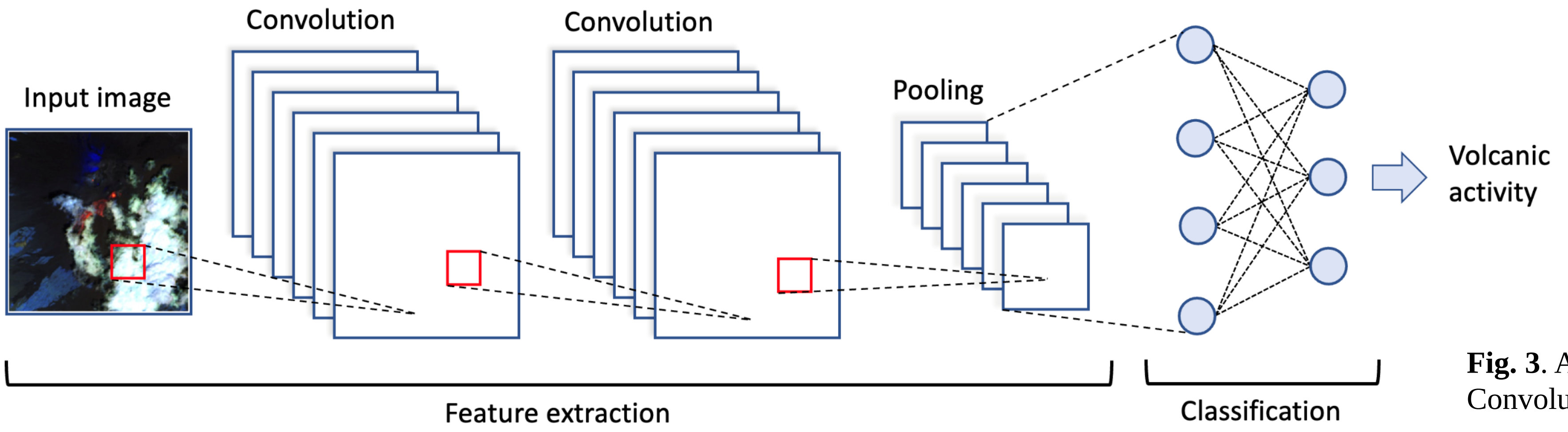

Fig. 3. Architecture of a Convolutional Neural Network

[2] Iandola et al. 2016, OpenReview
[3] Yang et al. 2020, Cambridge University Press
[4] Lin et al. 2017, IEEE Access

Performance analysis

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\#\ \text{samples}}$$

Global accuracy of 98.33% is achieved.

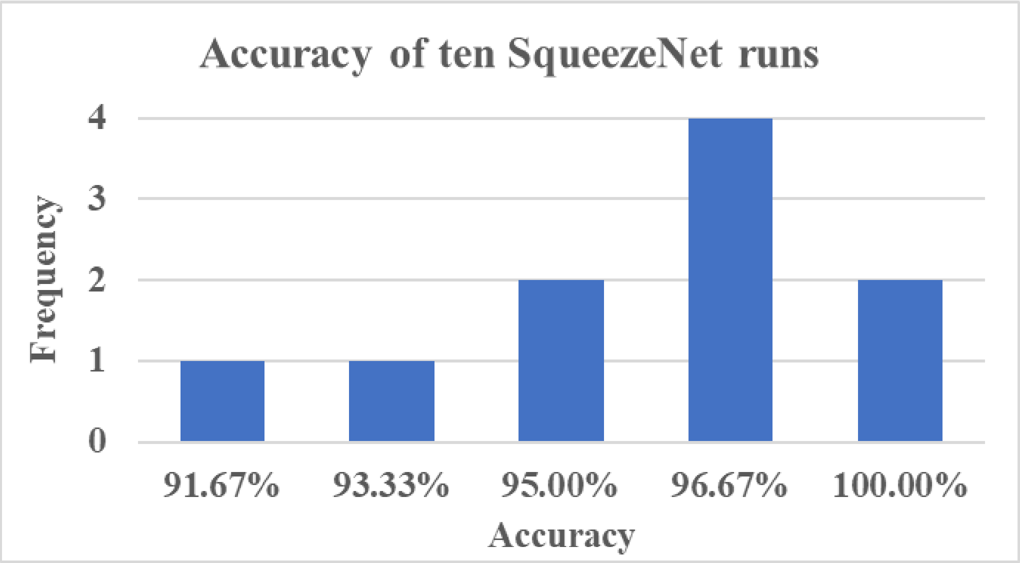

Fig. 4. Accuracies of the 10 runs of the trained SqueezeNet model.

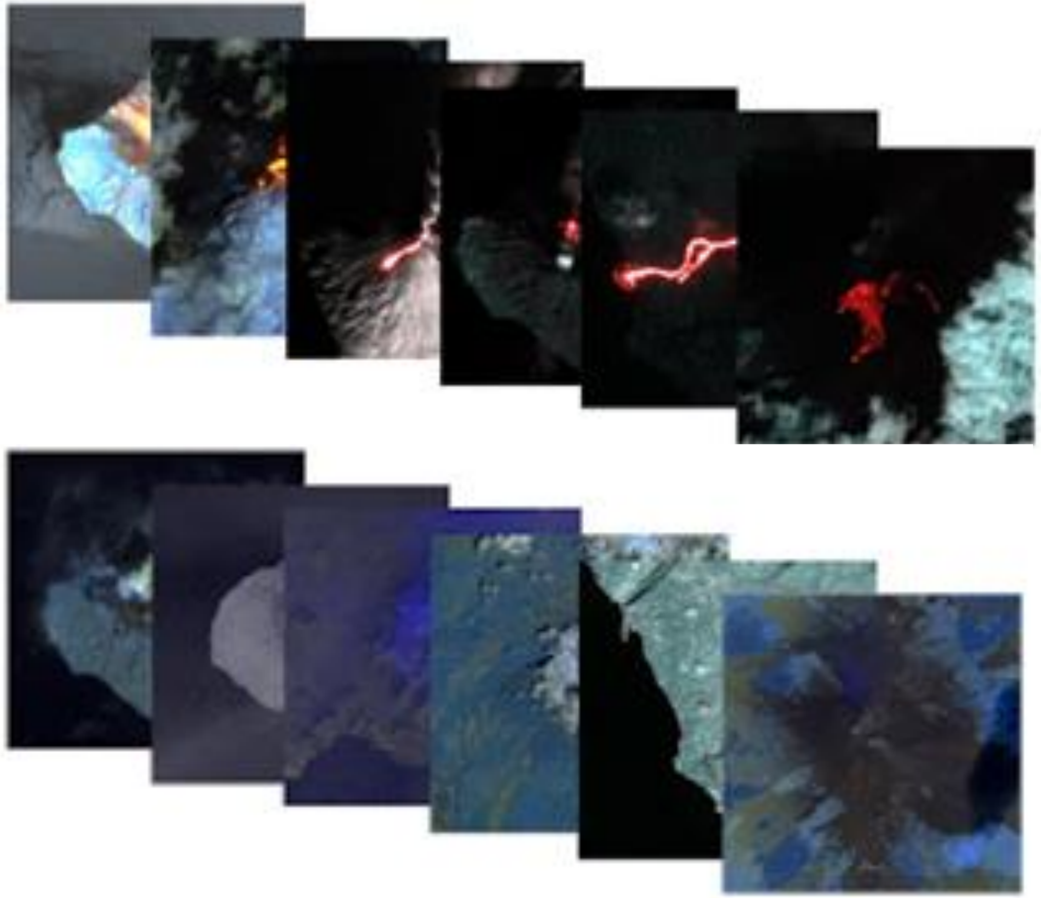

Fig. 5. Example of images for the two classes (up: “Yes Anomaly” ID 1, down: “No Anomaly” ID 0). All the images were captured via Google Earth Engine.

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Performance analysis

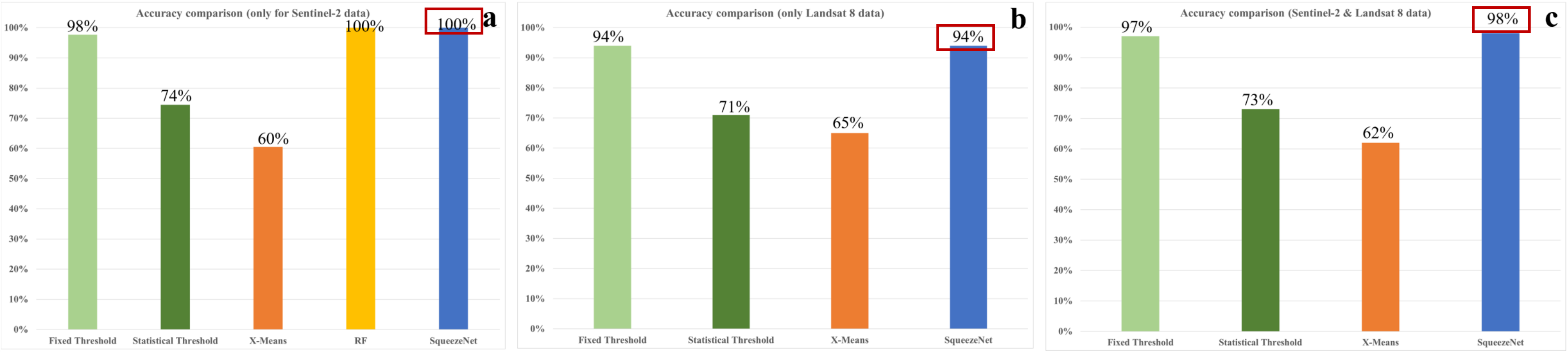
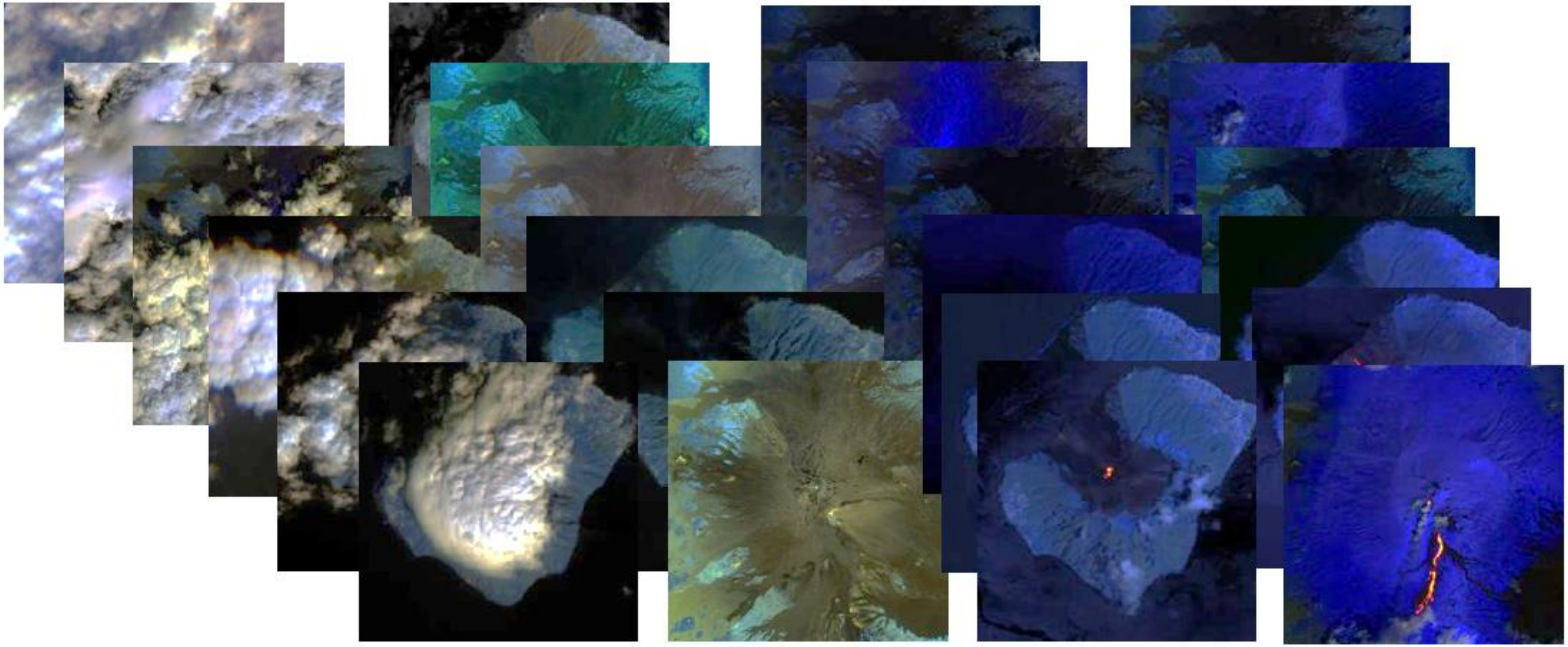


Fig. 6. Method comparison between fixed (light green bars) and statistical (dark green bars) thresholds, unsupervised (X-Means, orange bars) and supervised (RF, yellow bars) machine learning techniques and the SqueezeNet deep learning model (blue bars). (a) Only Sentinel-2 data, (b) only Landsat 8 data, and (c) both Sentinel-2 and Landsat 8 data. Note: RF trained only over S2 data.

The proposed model is readily available for S2 and L8 data, allowing to detect thermal anomalies, reducing the processing dead times, taking advantage of the first available acquisition between the S2-MSI and L8-OLI .

Next step

We are now working on a new development, including the identification of the type of activity (Poster ID: 167)



Class 0: Cloudy | Class 1: No Activity | Class 2: Thermal Anomalies | Class 3: Lava Flow

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Conclusions

- **High spatial resolution infrared satellite data** are fundamental to monitor hot temperature volcanic events;

- **CNN models** have been shown to overcome limits related to purely-intensity based approaches in detecting the presence of volcanic activity;

- The use of **transfer learning techniques** allows to greatly reduce computational cost and training time. The adoption of an **ensemble learning model** has allowed to achieve high accuracy, **98%**;

- Once trained, the proposed model can be applied to any of the available satellite radiometric scene captured by different satellite sensors over any volcano around the world in a few minutes;

- The results demonstrate the potential applicability of the proposed approach to the development of automated thermal analysis systems suitable for on-board data processing at global scale using future data coming from the planned missions, such as the NASA-ASI Surface Biology and Geology (SBG-Thermal), the CNES-ISRO Thermal infraRed Imaging Satellite for High-resolution Natural resource Assessment (TRISHNA), and the ESA-EC Land Surface Temperature Monitoring (LSTM).

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