Differentiating rock and soil types in thermal imagery with the use of CNN and ConvLSTM algorithms

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Contents

1 Introduction

A wide range of fields, such as geology, construction, urban planning, agriculture, or mining, rely on accurate knowledge of the ground. Therefore, it is necessary to develop useful and precise ground classification methods to help identify rocks and soils in a variety of contexts and conditions. Nowadays, there are many ways to achieve this through petrographic descriptions like texture and composition, anisotropy, QAPF diagrams, etc. However, there are still some areas that have been limited to the absence of interaction with rock or soil classification and that could leverage some promising results if applied correctly. As programming develops, so do the different ways in which information is handled, and as of today, artificial intelligence might be the key to new classification methods.

Thermal imagery is not often associated to any classification methods, for instance, in geology, where other more traditional methods are preferred. Thermal attributes in rocks and soils are influenced by many geological factors, which can be used to delineate a wide variety of them. Moreover, there are new technologies that provide new ways in which to collect and view thermal data due to the development of the aforementioned artificial intelligence, enabling for machine learning algorithms to take part in this classification process.

Deep learning is a newer type of data-driven machine learning which uses multiple neural network layers in order to obtain higher-level features from inputted datasets (Dehghani et al. (2023a)). It has had limited influence in rock and soil classification up to this date. Even though AI is growing at exponential rates and new algorithms are being developed to occupy such role, there is still limited implementation of thermal imagery in machine learning. Consequently, an objective of this thesis is to develop deep learning algorithms that manage to accurately classify a range of soils and rock types when receiving thermal data. By training and testing the algorithms, the aim is to take thermal attributes as inputs and yield the correct soil/rock type with the highest accuracy as possible in different contexts and environmental conditions.

The algorithms to be used in this project include Convolutional Neural Networks (CNN) and Convolutional LSTM (Long Short-Term Memory). CNNs are very powerful tools for extracting spatial features through filtering, acting as an initial classification method by recognizing different textures or patterns present in images. ConvLSTM algorithms are used to enhance the temporal analysis of sets of images, yielding temporal predictions that can identify the required features through their behavior over time. That being the case, these algorithms will be fed with either a single or a set of thermal images (both in the spatial and temporal domain) from which they will extract both the emissivity and the surface temperature values in order to classify different rock and soil types found in them. These algorithms will then be compared to provide insights into which one produces more accurate outputs. At the same time, the algorithms will be trained to work with a wide range of input images that include different environmental factors, such as diurnal and seasonal changes and different urban settings (to test how well it deals with several cities). The country this will be tested on is Spain, given its semi-arid conditions in order for vegetation or cloud coverage to not become a problem. However, if time allows it, to not limit the project to something regional, for instance, images from countries like the Netherlands could be used for training and testing the algorithms, given their different climate and ground composition. Thus, the algorithms would become more robust to cloud and vegetation coverage, resulting in a reliable tool for the scientific community.

The aim of this project is to develop a relevant classification process which aids in automating such a tedious process and acts as a pioneer for investigation on how AI with thermal images can improve fields like geology, providing a useful and modern link between the aforementioned geology and geomatics fields. For that reason, the research will determine if such an approach is viable as a classification method that may help make informed decisions in construction, landscaping or infrastructure projects. Thus, enhancing urban planning by detecting soil and rocks types in an automated way, contributing to more sustainable urban development, where infrastructures are placed on top of adequate soil. Moreover, reducing the risk of foundation failure or subsidence occurring due to erroneous human decisions. This can also be applied to other fields like mining (to avoid caves from collapsing), geology (detecting rock types in an efficient and faster way) or resource extraction (enhancing the efficiency of such process by reducing the cost of rock/soil identification).

2 Related work

The following section includes a small review of all the relevant information found in the literature with links to this project. Firstly, on thermal information and then on neural networks.

2.1 Relevant literature presentation

2.1.1 Understanding behavior of rocks/soils in thermal imagery

Ye et al. (2022) performed a study on emissivity and atmospheric parameters for estimation of land surface, where it is stated that remote sensing techniques involving TIR data contains information which helps distinguish features in the land surface, contributing to applications like land classification through differences in thermal attributes. Thus, implying the potential of implementing thermal satellite imagery for ground surface classification by accounting for different thermal attributes.

In Zhu et al. (2022), the study demonstrates the difference in thermal properties between rocks and soils. It is mentioned that igneous (1.93-3.14 W/m·K) and sedimentary (1.54-2.55 W/m·K) rocks tend to have higher thermal conductivity than looser sediments (0.89-1.82 W/m·K) due to their lower porosity. Nevertheless, it also shows how soils generally contain a better heat storage capability due to a larger water content, such as silt (1.80 MJ/$m^3 \cdot$ K) and clay (1.42 MJ/$m^3 \cdot$ K), exceeding most rock types. The analysis of the materials proves helpful for the thesis as a great source of information for developing hypotheses and knowledge on ground surface material thermal behavior.

Two studies proved how emissivity, although complicated at times, can be used as a suitable thermal attribute for differentiation of materials. In the first place, Guha and Kumar (2014) states that 0.96 is the acceptable approximated value for the emissivity of geological materials, influenced by their chemical composition. In the second place, Mineo and Pappalardo (2021) released a list of emissivity values from a wide variety of rocks. Mineo and Pappalardo (2021) proves that it is very difficult to obtain univocal emissivity values for rocks and that, instead, a range of these is used, where most of them fall between 0.83-0.99. Just as Guha and Kumar (2014), Mineo and Pappalardo (2021) also mentions how mineral composition affects the observations, where some minerals (michas) have higher surface temperature and, thus, emissivity is a weighted average of these minerals. Both of these papers contain emissivity values (for all the soil and rock categories to be used - defined later in section 4.1) which can be used as reference. They both make emphasis on the difficulty of using emissivity for classification purposes, given some value ranges between different rock types can be incredibly similar (sedimentary rocks = 0.91-0.99, igneous = 0.83-0.99, metamorphic = 0.89-0.99), leading to overlaps (stated as well in Rani et al. (2018),which mentions the sensitivity of temperature variations to land cover).

Harlianto et al. (2017) provide a guide into the main type of soil classification used. The USCS or Unified Soil Classification System. It classifies soils by using only two letters, the first one for the type of soil, and the second one for its plasticity or grain size. This classification serves as reference to the soil types to be used during the research.

Studies like Rockwell and Hofstra (2008b) and Guha and Kumar (2014) indicate the existence of several limitations when working with thermal images like ASTER's spatial resolution, which even though it shows potential for geological mapping, Rockwell and Hofstra (2008b) states that atmospheric correction is needed (such as MODTRAN). At the same time, Guha and Kumar (2014) describes the influence of vegetation cover on temperature values. Both of them give essential insights for practical considerations when working with this type of data.

SAR data will be implemented as a final complementary data type to enhance the classification process. SAR data can ease the process of finding differences in soil moisture values through time, which in combination with thermal attributes can result in more accurate outputs. Studies like Liu et al. (2019) (consisting of using LSTM for agricultural classification with SAR data) indicate that temporal dependencies in neural networks with SAR data improves the classification models. In turn, Ndikumana et al. (2018) integrate CNN to map land use and cover using SAR data, concluding how combining data types like optical and SAR improves effectively the classification process. Thus, the potential for SAR data to be used alongside another data type like thermal imagery.

2.1.2 Leverage of deep learning techniques

Regarding the machine learning aspect of the project, most of the information was achieved from documentations on CNN and ConvLSTM code and websites, but mostly from articles comparing and evaluating both methods. They provide information on how neural networks work and are structured with insights into how useful they are for classification.

The study from Yin et al. (2019) describes how CNNs and RNNs work, explaining how convolution takes place, what ResNets and BatchNormalization are used for, how ConvLSTM works and how the training process is conducted, taking care of overfitting and the outputs. Dehghani et al. (2023b) compares ConvLSTM and CNN models against each other and against° other types of neural networks in performance. The study concludes that CNNs and ConvLSTMs are the best at dealing with higher variations in data, providing excellent results for classification matters even when data is missing or there is great spatial distribution. In Ye et al. (2022), they propose a combined LSTM-CNN model for land surface parameters estimation with TASI imagery, in which they conclude that auxiliary data would enhance the classification accuracy of their model. Therefore, proving the potential of adding SAR data to the proposed models in order to obtain a much more accurate model.

2.2 Finding the gap

There are few studies that combine both emissivity and surface temperature values in an automated process that classifies rocks and soils types with two distinct deep learning algorithms.

Previous works mostly focus on just obtaining the thermal values and listing the outputs of each type (with very similar emissivity values). Others solely focus on implementing deep learning techniques to obtain different geological information.

Consequently, the thesis aims to fill this gap. Using emissivity and surface temperature to help identify different rocks and soil types through differentiating those small variances. Adding temporal dependencies, as well as the possibility of adding SAR data, can help with the identification process by distinguishing soil and rock types that have a similar range of thermal values but different temporal behaviors. To do so, geology, geomatics and machine learning will be combined in a process that will include knowledge all of these fields through different models (CNN and ConvLSTM) that manage to automate this process.

3 Research questions

The following section presents the main hypothesss and the research questions that guide the investigation. Given the aim of the project is to explore the potential of deep learning algorithms for the classification of rocks and soils with the use of thermal images, the following questions are designed to assess the effectiveness, accuracy and robustness of it. Answering these questions will be the foundation for determining the validity of the research. Only 2 soils types will be established at the moment for hypothesis. Nevertheless, the rest of rock and soil types will also have their respective hypothesis to help guide the experiments.

3.1 Hypotheses

- Clay soils gain heat slowly throughout the day but retain heat longer due to its higher moisture content and fine-grained texture.
- Clay soils are better identified when using both emissivity values and VV-polarization due to the higher moisture content returning a stronger VV back-scatter.
- Sandy soils gain heat quickly throughout the day but loose it rapidly given its lower moisture content and coarse-grained texture.
- Sandy soils are better identified in urban settings when combining thermal and SAR HH-polarization due to the HH-backscatter being stronger in these type of settings.

3.2 Research Questions

- To what extent can CNN-RNN combined deep learning methods help identify/detect different soil/rock types with thermal imagery?
- What characteristics/attributes do different rock and soil types have in thermal imagery?
- How accurately can temporally stacked CNN-based models vs. ConvLSTM identify rock and soil types with thermal attributes?
- How does the model deal with very similar rock/soil attributes?
- How do temporal factors (diurnal and seasonal changes) affect the classification performance?
- How do different urban settings affect the classification accuracy of the model?
- If other types of data are included (such as RADAR or SAR), does the performance/outcomes improve?

- When using SAR, what type of polarization (V-pol, H-pol) helps better in differentiation for soil types?

With all these questions in mind, it is important to state what will and will not be done during this project. Therefore, it is necessary to state the MoSCoW rules that will accompany the project. These set of rules give a clear idea as to how the research will be aimed.

3.3 MoSCoW Rules

3.3.1 Must

- Develop classification model.
- Train algorithm to identify different types of rock/soils.
- Train algorithm to handle temporal data to analyse changes over time.
- Handle data pre-processing pipelines to handle the noise, incomplete data or different resolutions.
- State the validity of the model (performance metrics).
- Incorporate and asses the impact of SAR data on classification performance.
- Test algorithm's ability to recognize under different conditions (diurnal, seasonal and urban settings).
- Analyze the effect of single vs. stacked spatio-temporal images for classification accuracy.

3.3.2 Should

- Compare results with complementary data.
- Investigate if simpler versions of the model can achieve similar results (ablation).

3.3.3 Could

- Test algorithm at different places (Spain, the Netherlands, Sahara).
- Test algorithm's ability to classify with increased vegetation or cloud coverage.
- Implement some physical sampling although the main focus remains on satellite imagery.

3.3.4 Won't

- Train algorithm to take color or geological properties into account (just work with thermal values).
- Focus on a single region or setting.
- Will not focus on a single specific rock or soil type.

These rules establishes the limits of the project. It is possible that some of them might not be accomplished due to time constraints on the project. Given there are many parameters, rocks and soils to test with, in addition to the time it takes to train such models, it could happen that some statements might not be met in time.

4 Methodology

The following section tackles the steps to be carried out to answer all research questions and develop the required models.

4.1 Methodology

The methodology established for the project is defined in a list of steps which represent an ideal workflow for the research to be accomplished before reaching the P4 and P5 deadlines (clearly established in chapter 5).

The first step is to define the problem (something established in chapter 1). Then, listing the rocks and soil types to be identified as well as the different conditions in which they will be tested. For soils:

- Sand
- Peat
- Clay
- Chalk
- Loam
- Silt

Rocks will be divided into three groups and, inside them, they will be further subdivided into two:

- **Sedimentary rock -** Carbonatic and Detritic
- **Igneous rock -** Plutonic and Volcanic
- **Metamorphic rock -** Foliated and Non-foliated

Later on, the corresponding datasets will be acquired. Labeled examples will be required to train the models to serve as reference for their performance. Data pre-processing of the images will be necessary for normalizing emissivity values (if necessary) by rescaling pixel values to be between 0 and 1, aligning them in temporal sequences or including code that deals with rotation, scaling and brightness of the images (to improve its performance against real-world conditions).

Further on, neural networks will be computed. In the first place, the Convolutional Neural Network. With a similar architecture to the one described in section 4.2, the convolutional layers will extract spatial features from the datasets, in this case emissivity (as the primary attribute) and surface temperature (as the secondary and complementary attribute). The decision behind these two attributes stems from the fact that emissivity is material-specific, thus is not that susceptible to environmental noise, and surface temperature can act as a great contextual factor. The algorithm will then be trained with different datasets to classify rock and soil types in individual thermal images. Separate subsets of the data will be used for validation. The program will later on be enhanced to intake stacks of images, and finally, multi-temporal images, testing any possible improvements in the identification process.

Secondly is the Convolutional Long Short-Term Memory algorithm. A defined temporal sequence of the images to be used as input is obtained. Convolutional operations will take place at different LSTM gates in order for the spatial context to be retained as the sequence advances. In these kind of neural networks, it is really important to avoid gradient problems as information travels backwards and forwards in the temporal sequence.

To test the robustness of the research, both algorithms will be put to the test with thermal images taken under varying environmental settings. The datasets will include images during diurnal and seasonal conditions, as well as different urban settings. The idea is that it can be used in as many contexts as possible, reducing its limitations.

Both models will be trained over a period of time of at least 15 days, so that they can absorb as much information as possible in the established timeline from section 5. Lastly, the algorithms will be monitored and their performance evaluated with metrics like accuracy, precision, recall or F1 score as the training process progresses. Confusion matrices will be used to identify any possible misclassifications taking place, early stopping for overfitting and temporal monitoring so that the sequence is checked consistently. The following three factors will be used as the main metrics:

- **OA (Overall Accuracy) -** states the amount of correctly identified rocks/soils divided by the total sample size of the dataset.
- **AA (Average Accuracy) -** indicates the precision across all different types of rock/soils used.
- **Kappa coefficient -** similar to confusion matrices, it represents the consistency of the true value against the classified one in all categories of the research (Zhang et al. (2023)).

To validate the results of the project, not only will performance metrics be used but also the comparison to other types of complementary data. Just like Rockwell and Hofstra (2008a) did, geological maps will be employed to compare the results, as well as SAR data being included to potentially enhance the performance of the models. This is because, given the similarities some rocks and soil types in emissivity and surface temperature profiles, the inclusion of SAR data can help, especially with soil grounds, in differentiating these cases over time.

Finally, both models will be compared to each other, testing for the highest accuracy model, with the most reliable outputs under all the established environmental and temporal conditions.

4.2 Architecture of NNs

The neural networks that will be employed will mainly rely on U-Nets, a simple architectural design for deep learning algorithms for image segmentation and which becomes very useful in cases like these where the aim is to output a type of structured data (images in this case) with the same spatial dimension as the input.

Regarding the first technique to be developed, the architectural design for the Convolutional Neural Network is based on the structure of the CNN in Dehghani et al. (2023a) and will be as follows:

- **Input layer -** initial layer adapted to accept thermal images as input.
- **Convolutional layers -** layers with multiple filters (kernels) that detect the wanted attributes/features in the images (textures, patterns, etc.).
- **Pooling layers -** same number of layers as convolutional ones. Will employ methods like max-pooling or average-pooling to reduce the spatial dimensions of images for further convolutional layers to act on, consequently controlling possible overfitting problems.

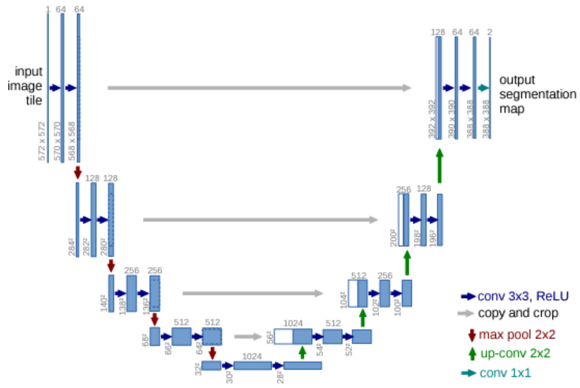


Figure 1: Architecture of U-Nets from Ronneberger et al. (2015).

- **Batch Normalization -** normalize the outputs to improve the convergence of the values.
- **Connected layer -** final fully connected layer flattens the feature maps generated with the previous layers, connecting them to a single dense layer that yields the classification made by the algorithm.
- **Loss function -** include a loss function (such as cross-entropy) that will measure the model's performance for specific tasks (in this case classification).
- **Optimizers -** including optimizers minimizes or maximizes a loss function by searching for the most optimal parameters (Desai (2020)). Thus, adjusting the learning rate for each parameter. Optimizers like Adam are suitable options.
- **Training -** the algorithm will be trained for sufficient epochs with an early stopping system in order to prevent overfitting problems.
- **Evaluation -** evaluate the performance, accuracy and adjust the hyperparameters of the model to obtain the best result possible.

For the architectural design of the ConvLSTM algorithm, a very similar process will be carried out. Shibuya and Hotta (2022) remarks, in his experimental study of combining convolution LSTM and U-Nets, the effectiveness of U-Nets in ConvLSTM for handling sequential data. Thus, a combination approach of the previous algorithm and that of Fig.2 will be carried out:

- **Input format -** input is formatted to become a sequence of images and an input shape (established with batch size, timesteps, channels, etc).
- **Input layer -** initial layer that will accept the sequence of thermal images.
- **ConvLSTM layers -** combine spatial feature extraction from convolutional operations with the LSTM gates that capture the temporal dependencies across the timesteps the algorithm retains the spatial context of the images.
- ResNets - integrated to avoid gradient problems like the vanishing gradient problem during backpropagation.
- **U-Net architecture -** this type of architecture handles the image segmentation while still maintaining the the spatial resolution. Through downsampling with convolutional and pooling steps, called the encoder path, the bottleneck is reached (lowest resolution where

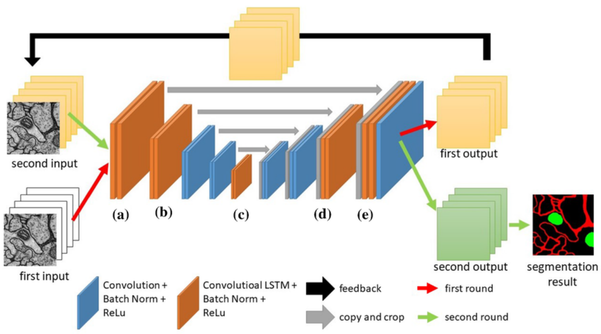


Figure 2: Feedback U-Net with convolutional LSTM from Shibuya and Hotta (2022). The output is fed to the input layer again once.

spatial features and temporal dependencies are merged). Then, the opposite step (unsampling) is carried out, until the original spatial dimensions are reconstructed. Connections can later be skipped by passing information from the encoder to the decoder (Shibuya and Hotta (2022)) while preserving finer details.

- **Pooling layers -** optional layer to reduce the time dimension of images (max-pooling for instance).
- **Dense layer -** a layer that will flatten the output and feed it into a single dense layer yielding the final classification established by the model.
- **Loss function -** similar to CNN model.
- **Optimizers -** same as CNN model.
- **Training -** model training for enough epochs with controlled overfitting problems.

4.3 Code structure

The main idea of the code structure can be observed in the GitHub for this project: `https://github.com/Javif16/geo2020_Javier_Martinez.git`. Currently, the code structure includes the files below, but note that changes may occur as the code is developed during the research process.

The idea is to have each section of the project have its own python file:

- **thermal.py -** deals with normalizing the initial datasets, making them suitable for the neural networks.
- **CNN.py -** Convolutional Neural Network, as well as training and parametrization.
- **ConvLSTM.py -** Convolutional Long Short-Term Memory, as well as training and parametrization.
- **performance.py -** the program will test the performance for any algorithm inputted, through the metrics established in section 4.1.
- **complementary.py -** with additional conditions and cases, it will include all possible cases the models should be able to deal with, such as varying urban settings. In addition, it will contain any necessary code for the inclusion of SAR data.

5 Time planning

To explain the time planning behind it, a Gantt chart has been developed to explain, with visual detail, the timeline for this research:

As it can be observed in Fig.3, the timeline is divided in 5 main parts (differentiated by colors), each one corresponding to a different deadline or phase.

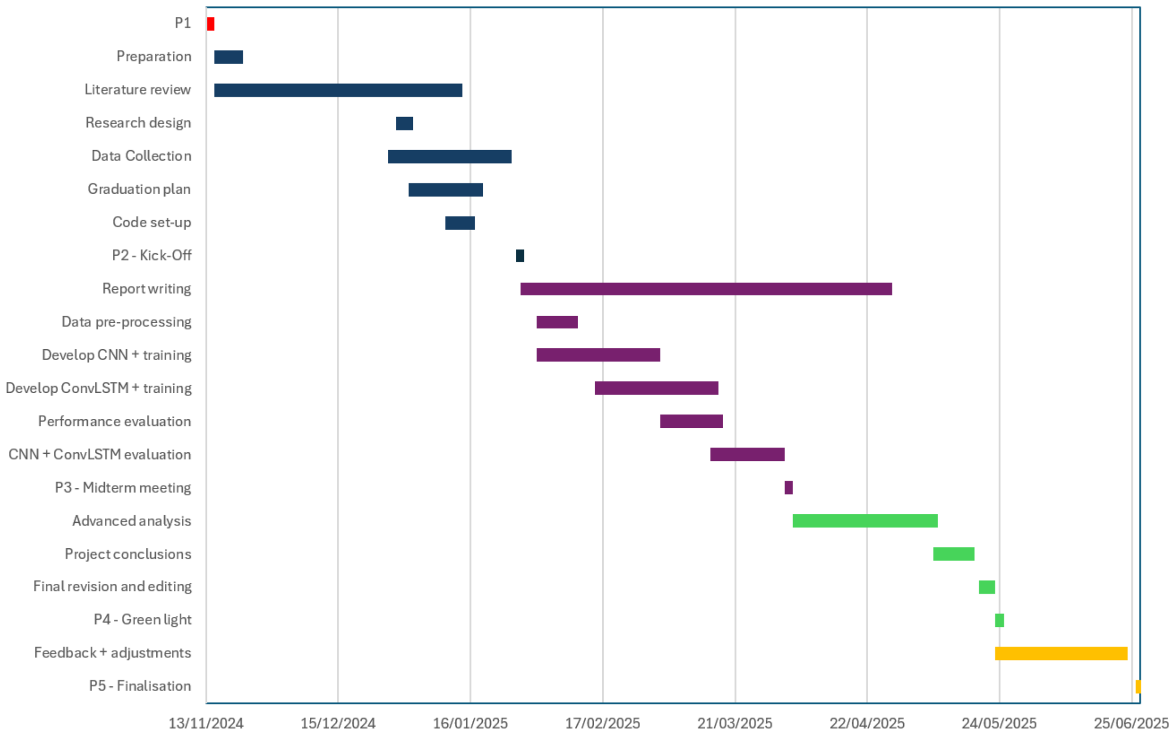


Figure 3: Gantt chart of thesis project. Each color corresponds to a different phase of the research process (P1, P2, etc.)

5.1 P1

The requirements for this phase had already been met during November, at the start of the Thesis Preparation course.

5.2 P2 - Kick-off

- **Preparation -** identifying the research topic, the gap, the problem and the objective. In addition, developing the hypothesis and research questions by exploring the relevant literature.
- **Literature review -** knowledge of deep learning techniques and thermal data. Understanding what results to expect when completing the research.
- **Research design -** deciding on methodology and the steps to be taken.
- **Data Collection -** collecting the necessary data and establish where the datasets will be obtained from.
- **Writing -** outlining chapters and writing draft report.

- **Code set-up -** developing coding environment, code structure, organization, etc.
- **P2/Kick-off -** presentation of Graduation Plan and decision.

5.3 P3 - Midterm

- **Develop CNN -** Convolutional Neural Network model, testing and training thermal datasets.
- **Develop ConvLSTM -** Convolutional Long Short-Term Memory model, testing and training with thermal datasets.
- **Performance evaluation -** evaluating performance.
- **CNN-ConvLSTM evaluation -** determining the feasibility of both models for the research's purposes.
- **P3/Midterm meeting -** meeting with supervisors to check progress.

5.4 P4 - Green light

- **Advanced analysis -** enhanced analysis as networks are optimized and trained with complementary data (SAR).
- **Project conclusions -** obtain final feasibility conclusion. Present results and potential future work.
- **Final revising and editing -** last adjustments on draft report.
- **P4/Green light -** presentation of draft thesis report and final decision.

5.5 P5 - Finalization

- **Feedback & adjustments -** necessary changes to the project, enhancing code and finalizing the draft report with feedback from P4.
- **P5/Finalization -** final presentation of the project.

6 Tools and datasets used

The following sections explains the tools and datasets that will be employed during the research in order to fulfill all the objectives set. The code will be performed in Python language, given its wide range of community libraries. Thermal data will be obtained from several resources and in different formats and resolutions, to test which one performs the best.

The python files established in the GitHub in section 4.3 may be carried out either in *PyCharm Community* or in *JupyterNotebook* (as its division in blocks reduces computational time), depending on how fast the algorithms run on the local *PyCharm*.

6.1 Python libraries

The main libraries that will be used for coding, building and training the algorithms are *PyTorch* and *TensorFlow*, given their wide range of functions specialized on deep learning operations. Both will be included in order to get the most out of the algorithms.

Other important libraries that will be employed are *'Rasterio'*, for reading and writing geospatial data, *'Numpy'* for any mathematical operation, as well as *'Matplotlib'*, *'IPython'* and *'ipywidgets'* to visualize the results.

Finally, sub-libraries stemming from *TensorFlow* will most likely be included in the project to deal with the neural networks. For example, *'Keras'* includes many functionalities to build and train deep learning algorithms like ConvLSTMs, easing the process of generating such a complex program.

Here is an example, from the *Keras* documentation website (Team (2025)):

Listing 1: ConvLSTM2D Code Example

```
x = layers.ConvLSTM2D(
    filters=64,
    kernel_size=(5, 5),
    padding="same",
    return_sequences=True,
    activation="relu",
)(inp)
x = layers.BatchNormalization()(x)
x = layers.ConvLSTM2D(
    filters=64,
    kernel_size=(3, 3),
    padding="same",
    return_sequences=True,
    activation="relu",
)(x)
```

These libraries allow for a seamless integration of a variety of machine learning operations and techniques. Thus, functionalities like batch normalization, activation and loss functions can be implemented with them.

6.2 Thermal datasets and Data Acquisition

Thermal datasets will be obtained from open access portals, mainly from the USGS Earth Explorer (Landsat 8-9) and NASA's EarthData Search (ECOSTRESS). The portals include imagery from the Landsat 8-9 OLI/TIRS (Operational Land Imager/Thermal Infrared Sensor) C2 (Collection 2) L1 and L2 (product levels) and ECOSTRESS, respectively. USGS's portal contains data from Operational Land Imager-2 (OLI-2) and Thermal Infrared Sensor-2 (TIRS-2), which acquires multi-spectral observations of the Earth (Choate et al. (2023)) in L1 (corrected to a standard map projection) and L2 (contains atmospheric and additional corrections) products. From Earth Explorer, the data is obtained in GeoTIFF or JPEG format (thus, the use of *Rasterio*), with a resolution of 100 meters for thermal bands (Bands 10 and 11).

NASA's portal provides ECOSTRESS (ECOsystem Spaceborn Thermal Radiometer Experiment on Space Station) outputs with thermal data at a resolution of 70 meters in TIF format. It also contains ASTER data. ASTER or Advanced Spaceborn Thermal Emission and Reflection Radiometer contains fine spectral bands in short-wave infrared (SWIR) and thermal infrared (TIR) regions of the electromagnetic spectrum (Fatima et al. (2017)). The portal contains ASTER L2 data (which is used for geological mapping as Rockwell and Hofstra (2008a) did), for both surface temperature and emissivity in independent files. However, in this case, all the files are obtained in 'hdf' format. In Figures 4 and 5 are some example datasets.

SAR data will be obtained from ESA's Copernicus Open Hub. A portal that contains SAR data in different formats, either in raw data for better custom analysis or with the already pre-processed GRDH data. It will be a valuable tool to be used in the later stages of the research to enhance classification accuracy.

Python libraries like *Rasterio*, *Numpy* and additional ones such as *GDAL* (Geospatial Data Abstraction Library) will be used to handle GeoTIFF files, 'h5py', to handle 'hdf' files, and possibly '*Xarray*' to deal with multi-dimensional arrays.

During the normalization steps, *Numpy* and *OpenCV* can handle image pre-processing like resizing, cropping or other basic operations. Then, when the single images turn into temporal sequences, libraries like *Pandas* or *Xarray* will ensure the sequence order is maintained. Batching will be handled by libraries like *PyTorch* and *TensorFlow*, while visualization will take place mostly with *Matplotlib*.

6.3 Data Preparation

Data cleaning is a necessary step to providing relevant datasets for the neural network models. Corrupted or incomplete data must be removed, or with the use of QA bands from Landsat data, clouds and shadows can be identified and masked (including other possible artifacts found in the data). Data should also be transformed if necessary, such as resampling or resizing, especially if obtaining datasets from different sources (which might be this project's case) and formats. Using *GDAL* or *Rasterio* can help maintain consistent data inputs with the same coordinate reference system or unit conversion, for instance, changing surface temperature or emissivity values to [0, 1] (with *Numpy*), respectively. At the same time, libraries like *OpenCV* can ensure that rotations or flips are dealt with correctly before inputting them into the algorithms. The temporal sequences will be transformed from single images that will be stacked together. To do so, *Pandas* and *Xarray* can help cluster these images by time intervals and maintaining chronological order.

Lastly, dividing the datasets will be crucial for training the models. Thus, a suitable range of training and testing for the project is 70%-30%, respectively (the number can change if datasets become too big and training needs to be maximized). In each division, a balanced representation of rocks and soils must be ensured, in order for the training to be as successful as possible. Temporal considerations will also be accounted for, in order for time series to not be very different between subsets. If possible, Landsat and ECOSTRESS data could be merged or combined with the purpose of including more information into the final dataset, though this is an experimental note.

7 Preliminary results

The outcomes of the thesis aim or are expected to demonstrate the feasibility and effectiveness of employing CNN and ConvLSTM for classifying rocks and soils based on thermal attributes. However, some of the expected results at the moment might not be achieved at the final stages of the research due to time constraints. A feasibility study will be carried out, in which testing if the method to differentiate rock and soil types in this way is actually possible.

7.1 Expected Algorithm Performance

7.1.1 CNN

The model is expected to perform correct spatial classification of rocks and soils from the thermal attributes extracted from the images (for instance, differentiating clay from loam or volcanic from plutonic). First for a single image and, later on, for a whole set of thermal images. However, given the similarity in the emissivity ranges the rocks have, overlaps can become a big problem. Nevertheless, the aim is for the program to obtain high performance metrics with values >=85% or >=0.85 (for the main metrics established in section 4.1).

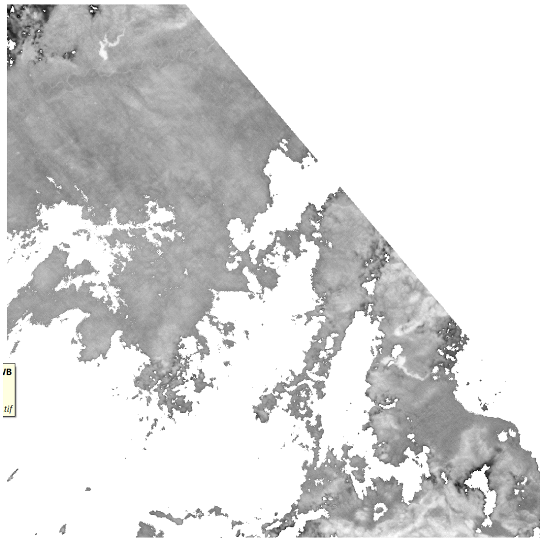
7.1.2 ConvLSTM

This model should be expected to produce a similar performance to that of the CNN, performing a correct temporal classification, enhancing the process by identifying temporal patterns that can help detect variations between different types of rocks and soils (such as slower/-faster cooling rates). Just as with the CNN model, it is expected to produce performance metrics higher than >=85% or >=0.85.

7.2 Thermal datasets

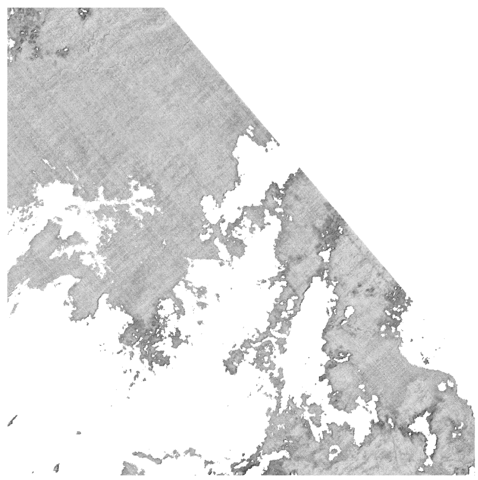
This section displays some example images of thermal data that will be used to train and test the algorithms presented in the project (obtained from the portals mentioned in section 6. These images can also be observed in the GitHub of this project, mentioned in 4.3. It includes initial preliminary code of how data is normalized from the thermal images found in the following path: Set-up/Thesis/Thesis/thermal.py. In this same path, two files with the outputs of the code can be found, with the values for emissivity and surface temperature already normalized. It also includes the rest of the thermal images obtained at the moment, found in the following path: Set-up/Thesis/Thesis/Images/Thermal.

In the following images, both bands 10 and 11 from LANDSAT are presented, as well as ECOSTRESS. The main candidates for the research are Band 10 from LANDSAT (less affected by atmospheric interferences) and ECOSTRESS images (higher spatial resolution). Band 11 will be used, if necessary, as complementary data. The resolution differences will be pre-processed before inputting the datasets into the algorithms.



(a) Land Surface Temperature (LST) image of ECOSTRESS data from the 18th of December 2024.

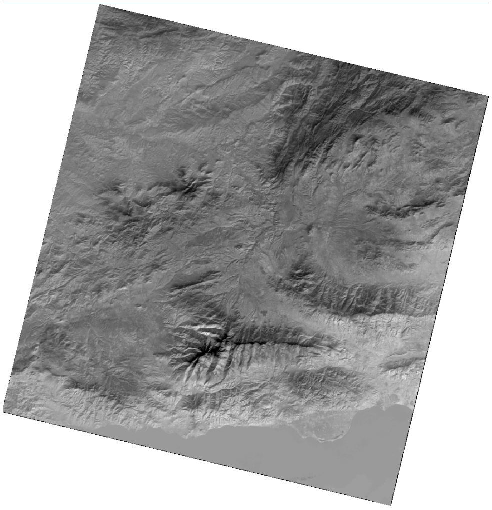
(b) Emissivity image of ECOSTRESS data from the 17th of November 2024.



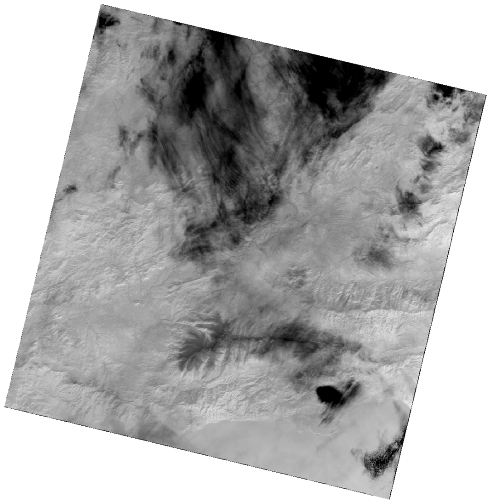
(c) Emissivity image of ECOSTRESS data from the 18th of December 2024.

(d) Emissivity images of ECOSTRESS data.

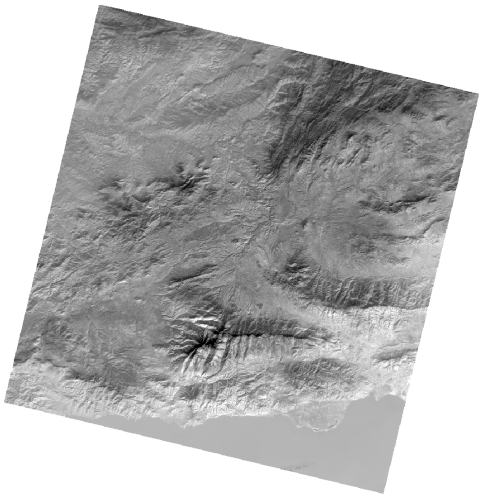
Figure 4: ECOSTRESS images showing Land Surface Temperature (LST) and Emissivity data for different dates.



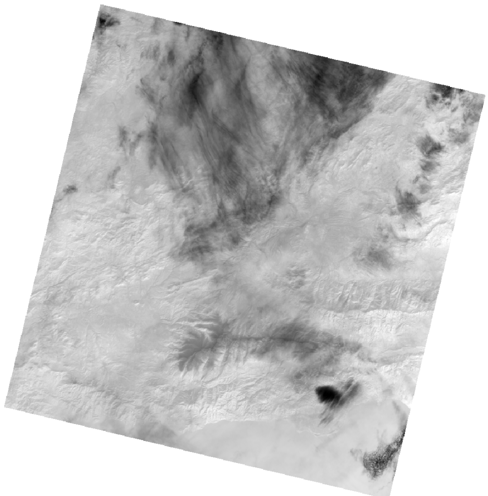
(a) Thermal image from the 23rd of December 2024.



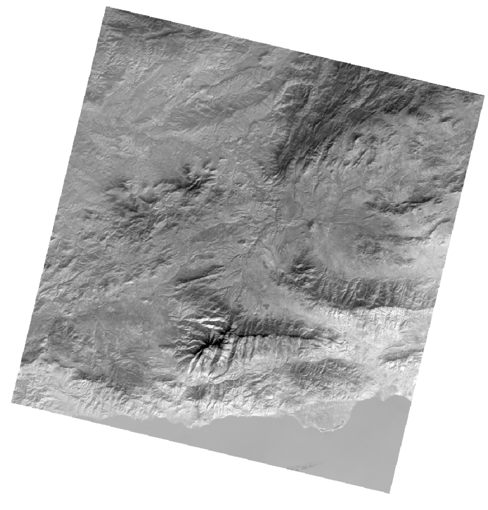
(b) Thermal image from the 8th of January 2025.



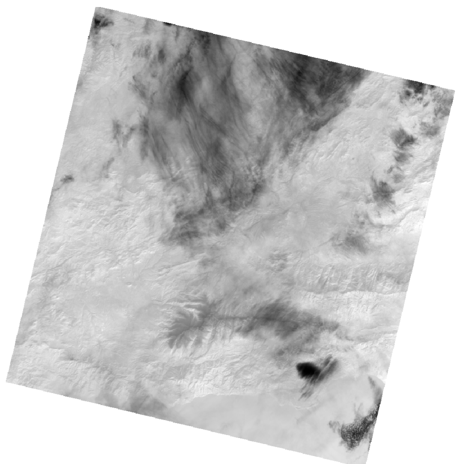
(c) Thermal image of Band 10 from the 23rd of December 2024.



(d) Thermal image of Band 10 from the 8th of January 2025.



(e) Thermal image of Band 11 from the 23rd of December 2024.



(f) Thermal image of Band 11 from the 8th of January 2025.

Figure 5: Landsat images showing thermal data for different bands (B10, B11) from various dates.

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