# USING SNN NEURAL NETWORKS TRAINED WITH HIGH RESOLUTION DATA 2 AND APPLIED TO COPERNICUS SENTINEL-2 DATA

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**ABSTRACT:**

Data from the Copernicus project are proving to be fundamental in so many areas of spatial governance, and in particular in the context of safeguarding the cultural and natural heritage. This is mainly due to their dissemination mode, which allows them to be used by a countless number of institutions and organizations. With regard to their use in order to create effective supervised-training AI (Artificial Intelligence) classifiers (useful for continuous land-use monitoring), their low resolution could be a problem in terms of accuracy or in any case during the training process. This process which could be very costly (large training sets and high-end hardware required). In this paper, a methodology is tested that creates an AI classifier from high-resolution training data, Remote Sensing Image Classification Benchmark (RSI-CB128) and using Self-Normalising Neural Networks (SNNs). The efficiency of the Neural Network is, however, measured with a test dataset constructed with Raster Sentinel-2. In other words, the aim is to assess the goodness of an AI classifier on Sentinel-2 images built from Rasters generated by high-resolution sensors. Therefore, there seem to be clear advantages over the classification methodologies in use today.

## 1. INTRODUCTION

Copernicus satellite data is a source of information collected by a series of satellites operated by the European Space Agency (ESA) in collaboration with the European Union. These satellites form the core of the EU's Copernicus program, which provides a wide range of data on the Earth and its activities. As known, Copernicus data covers a wide range of topics, including:

- Environment and climate: Copernicus satellite data are used to monitor climate change, weather conditions, air and water quality, land cover, and biodiversity.
- Land management: Copernicus satellite data are used to map the territory, monitor land use, manage natural resources, agricultural activities, and urban planning.
- Safety and emergency management: Copernicus satellite data are used to monitor potentially dangerous human activities, such as migration movements, traffic routes, and fishing activities, as well as to monitor natural disasters such as fires, floods, and earthquakes.
- Transportation and infrastructure: Copernicus satellite data are used to monitor traffic flows, manage ports, and transportation infrastructure.
- Public health: Copernicus satellite data are used to monitor air and water quality, as well as to detect sources of pollution.

As well know, Copernicus satellite data is accessible for free through the ESA's Open Access Hub portal. The resolution of Copernicus data varies depending on the type of sensor used and the frequency of data acquisition. For example, optical sensors on board Sentinel-2 and Sentinel-3 satellites can acquire images at resolutions ranging from 10 to 300 meters, while synthetic aperture radar (SAR) on Sentinel-1 satellites can acquire data at resolutions ranging from 5 to 100 meters. The protection of environmental and cultural assets can only be effectively implemented if a great variety and number of authorities, institutions and even private individuals are involved in the monitoring and conservation processes (Barrile & Bilotta, 2016) (Bilotta, Calcagno & Bonfa, 2021) (Angiulli, Barrile, Cacciola, 2005) (Barrile, Bilotta & Pannuti, 2008) (Barrile & Bilotta, 2008). In this sense, the data of the Copernicus project are a fundamental tool, in fact, their modality of dissemination (free of charge and update times) can guarantee that all the actors proposed to the government of the territory can detect any changes on the ground in time and plan a strategy in response to them (Salgueiro, Marcello, & Vilaplana, 2021). Broad participation in such a safeguarding process is only possible if, in addition to data, analysis tools are equally accessible in terms of quality and cost.

Satellite images can be classified using different methodologies (such as the Bayes classifier, the Maximum Likelihood classifier, Decision Trees, Neural Networks, and Support Vector Machines). With regard to some of these, a further subdivision can be made between Object/Pixel based and supervised and unsupervised classification. In particular, supervised classification involves the user manually selecting some areas of the image (known as "training areas") and assigning them to a specific class, such as "forest", "water", "urban area", etc. The classification software then uses these training areas to automatically identify other areas of the image that correspond to the same class. Unsupervised classification, on the other hand, uses clustering algorithms to automatically identify the different classes present in the image. The classification software analyzes the image and automatically identifies groups of pixels with similar properties, which are then assigned to specific classes. In both cases, the accuracy of the classification depends on the quality of the images, the quantity

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and quality of the training areas, and the type of classification algorithms used.
In terms of IT tools, AI (Artificial Intelligence) classifiers appear to be particularly performing and can be used to identify the evolution of critical phenomena through the analysis of Sentinel-2 images: Desertification, Coastal Erosion, Availability of Water Resources, Green Spaces and the like. The construction of an AI classifier that gradually incorporates new categories and situations can be problematic for small entities when such a process requires large volumes of learning data to obtain a high precision classifier (Ben Hamida, Benoit, Lambert & Ben Amar, 2018) and consequently very expensive hardware, together with specialized technical capabilities (e.g. High-Performance Computing - HPC equipment management, Field-Programmable Gate Array - FPGA, Cloud Computing). HPCs differ from traditional computers due to their highly specialized architecture, consisting of multi-core processors, hardware accelerators, and high-speed system memory, which enables them to process large amounts of data in a very short time. Unfortunately, this could be the case with Sentinel data, where a low spatial resolution could lead to the creation of training sets affected by labelling errors (e.g. image classification by a human). It is well known that one of the advantages of neural networks is that they are resistant to 'noise' (Ding, Cheng, Cheng, Li, You & Yuan, 2017) (even in the training phase), but only if there are large training sets. In addition, high-resolution raster provides semantically less ambiguous spectra. The aim of our work is to investigate how an AI classifier trained with freely available high spatial resolution data, that is the Remote Sensing Image Classification Benchmark. As known, there are two datasets: RSI-CB256 dataset and RSI-CB128 dataset (Li, Dou, Tao, Wu, Chen, Peng, et al., 2020). RSI-CB256 is a satellite imagery dataset developed to evaluate the performance of image classification algorithms. The dataset is composed of satellite images acquired from various sources, with a spatial resolution of 256 x 256 pixels and 16 bits per channel. The dataset consists of 21,061 images divided into 45 classes, including trees, roads, buildings, crop fields, water and more. RSI-CB128 dataset consists of a catalog of 36,000 images with a spatial resolution of 3 meters, the images are 128 x 128 pixels. The images were acquired in different weather conditions, seasons and time zones, and cover different geographical areas, including forests, crops, urban areas and water. Each image is associated with a ground truth classification map, which indicates the classes present in the image. Specifically, the RSI-CB128 built with equally accessible tools (Tensorflow) and used with Sentinel-2 data for evaluating and comparing the performance of remote sensing image classification algorithms was used. The dataset for the Sentinel-2 data in our work was acquired from the Kaggle platform, a web portal specialising in managing professional training set data. The name of the catalogue is EuroSat Dataset. It consists of 27,000 images at 10 meters resolution, each image is 64x64 pixels. The bands taken into account are RGB and the categories used are those most useful for safeguarding environmental assets. In this specific case, for the testing of the methodology, the software used is Tensorflow by choosing a neural network of type SNN (Self-normalising Neural Networks) (Klambauer, Unterthiner, Mayr, Hochreiter, 2017) for the classification.

### 1.1 Using SNN Neural Networks with 'SELUs' Layer

During experimentation, when training neural networks, only SNNs with at least one layer made up of neurons with a SELUs (Scaled exponential linear units) activation function (Klambauer, Unterthiner, Mayr & Hochreiter, 2017) were used. SNNs have as their main characteristic the fact of being self-normalizing neural networks and therefore do not require preprocessing of inputs with scaling/normalization activities or batch processes. The heart of this type of network is the use of the SELU activation function, which in addition to guaranteeing the property of self-normalization of the data guarantees convergence towards the zero mean and unitary variance in training errors, convergence in the training process is so accelerated, you don't need to do continuous random initializations to avoid local minima. Therefore, the SELU learns faster and better than other activation functions without the need for further processing, and this is especially true when the training set is quite noisy. This type of activation function has been introduced very recently in the AI landscape and was chosen here mainly due to its high performance in the learning phase and the fact that it does not require any kind of normalisation of the input data, which is why such networks are referred to as Self-normalising Neural Networks (Huang, Ng, Liu, Mason, Zhuang, & Liu, 2020). Its form and expression are shown in Figure 1.

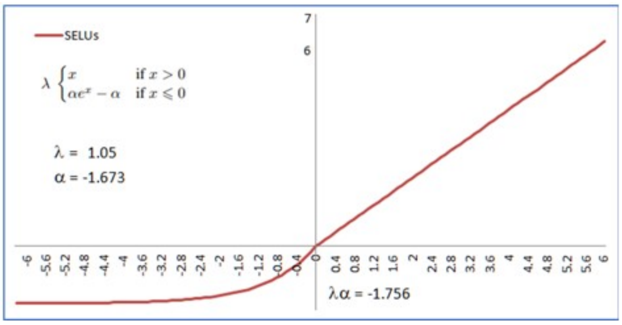


Figure 1: SELUs (Scaled exponential linear units) activation function used for Self-normalizing Neural Networks.

The "SELU" non-linearity keeps the data standardized and the gradients from getting too small or too large. The effects are comparable to batch normalization while requiring significantly less computation. Furthermore, the convergence property of SNNs towards zero mean and unit variance allows training of deep networks with many levels and makes learning extremely solid. The SELUs activation function offers considerable advantages that make it preferable even to RELUs (Rectified Linear Units) (Rasamoelina, Adjailia & Sinčák, 2020) the latter being widely used within CNN convolutional networks (Ide & Kurita, 2017) . Some of the advantages include:

- They make the network self-normalising;
- SELUs does not have vanishing gradient problem;
- Compared to ReLUs, SELUs neurons cannot die;
- SELUs learn faster and better than other activating functions without the need for further processing.

The parameterisation in figure 1 is the default defined in the design environment and is taken from the literature.

## 2. MATERIALS AND METHODS

The main aim of this work is to investigate the behaviour of SNN Neural Networks - SELUs when trained on a high-resolution RSI-CB128 dataset (SNN (RSI-CB128)) but tested and applied to Sentinel-2 image classifications (Kaggle EuroSat Dataset).
The aim is therefore to make it possible to evaluate the idea of

profitably using AI (SNN) classifiers on Sentinel-2 images, when these are built on a publicly available, up-to-date dataset built on high spatial resolution images. This is specifically in the case of environmental and cultural monitoring. The use of remote sensing allows obtaining information over large areas quickly and efficiently, reducing the costs and time required for field sampling. In addition, the availability of historical images allows monitoring the evolution of the environment over time and evaluating the effectiveness of land management policies.
The methodology involves different steps, described in the Figure 2 below.

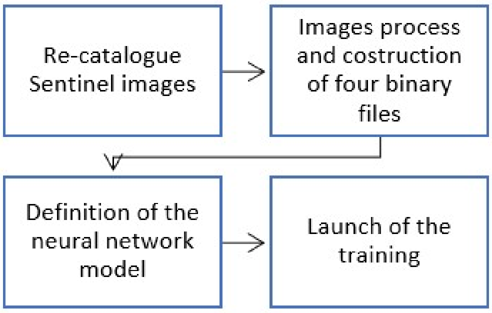


Figure 2: Methodology used in the study.

The first step was to re-catalogue the Sentinel images used in the two datasets into:

1. Lakes
2. Sea (including coastal areas)
3. Desert
4. Green areas
5. Residential areas
6. Infrastructure
7. Cultivated fields

The choice fell on these categories because of the monitoring useful for the early detection of critical issues such as coastal erosion, urban sprawl, desertification, reduction of green areas, water shortage. In fact, they represent important environmental problems that threaten the survival of the Earth's ecosystem and the quality of human life. These problems have long-term effects and can cause irreversible damage to the environment and biodiversity, as well as have significant social and economic impacts. Additionally, these critical issues are often interconnected, and their consequences can worsen each other. Figure 3 shows a synthetic mosaic of these categories. Having defined these classes, we moved on (second step) to process the images and construct four binary files from them:

- Training set using RSI-CB128 data (15000 Records);
- Test set using RSI-CB128 data (1000 Records);
- Training set using Kaggle Sentinel-2 data (15000 Records);
- Test set using Kaggle Sentinel-2 data (1000 Records).

The aim was to construct two Neural Networks (SNNs), one, as mentioned, with the RSI-CB128 data for the construction of the classifier (Figure 4), but also a second one using the Sentinel-2 data in order to make cross comparisons at the time of testing (Figure 5).

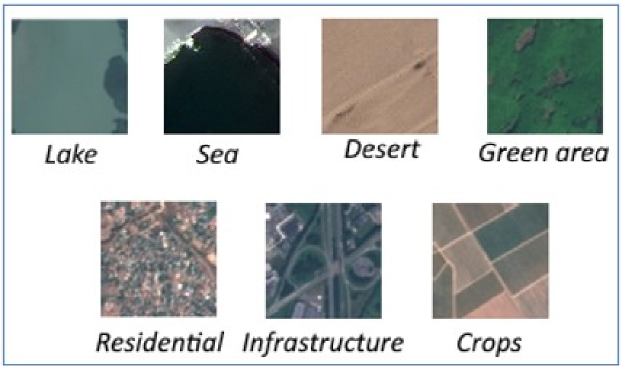


Figure 3: Examples of images belonging to the selected classes.

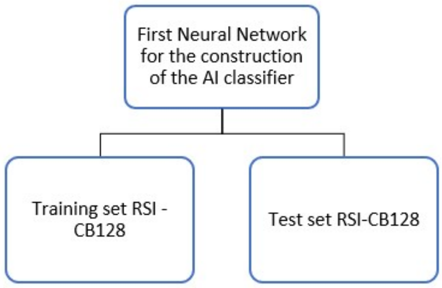


Figure 4: First Neural Network for the AI classifier.

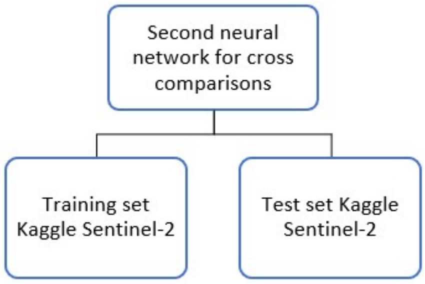


Figure 5: Second Neural Network for cross comparisons.

Then, we defined (third step) the neural network model. A number of inputs equal to 20x20x3 (Matrix of Pixels of 20 units and the three RGB channels) were then defined for both networks. It should be noted that the central part of the images was stretched. Image stretching is often used in image classification to improve the visualization and analysis of information present in the image. Stretching can increase the contrast of the image and improve the distinction between different areas of the image, making it easier to identify image features used for classification. Additionally, image stretching can also improve the effectiveness of some image processing techniques, such as segmentation and feature extraction. In general, image stretching can be useful in improving the accuracy of image classification and reducing classification errors caused by the presence of noise or variations in image brightness. Also, crucially, no upscaling or downscaling was performed to make alignments between the different spatial resolutions. This means that the individual images of the datasets (regardless of the area covered) represent a single class, or rather, a single semantic unit. The two neural networks were also constructed in the same way:

- Input Layer (DensData);
- Linear Activation Function Layer (500 neurons);

- DropOut Layer. With 30% activation rate. Layer only present during training, helps prevent overfitting;
- Layer with SELUs activation function;
- Linear output layer with 7 outputs.

Finally, as step four, training was launched. The training time with the RSI-CB128 dataset was 2 hours and 10 minutes, while the training time with the Kaggle Sentinel-2 dataset was 2 hours and 40 minutes. The same workstation with 8 logic processors (11th generation Intel core i7) was used for both training phases.

## 3. RESULTS

Once the training was finished, comparisons were made through a comparison among the classification error rate on the test sets. Cases considered:

- AI Classifier (RSI-CB128 data) - Test set RSI-CB128, error: 0.8 %
- AI Classifier (Kaggle Sentinel-2) - Test set Kaggle Sentinel-2 , error: 3 %
- AI Classifier (RSI-CB128 data) - Test set Kaggle Sentinel-2, error: 1.3 %

Figure 6 summarizes the results listed above.

| AI Classifier | Test set | Error |
|---|---|---|
| *RSI-CB128* | *RSI-CB128* | *0.8%* |
| *Kaggle Sentinel-2* | *Kaggle Sentinel-2* | *3%* |
| *RSI-CB128* | *Kaggle Sentinel-2* | 1.3% |

Figure 6: Comparison between classifiers and test sets.

The third case is certainly of greater interest, showing how the classifier AI (RSI-CB128 data) with SNN - SELUs can be profitably applied to the Sentinel-2 data. This consideration also finds strength in the second case, in fact with the same model, the neural network trained with the Kaggle Sentinel-2 data shows larger errors on the test set extracted from its own data set used for its training.

To evaluate the reliability of the proposed methodology (SNN (RSI-CB128)) the average values of the comparisons are shown in the following table (Figure 7) (evaluating the performance as the number of randomly sampled pixels varies and as the classifiers vary, both in terms of percentage errors both in terms of errors of the first and second type of the error matrix) with other more commonly used segmentation/classification techniques carried out on different parts of the images, also making reference to the parameters ACC (Accuracy), SEN (Sensitivity), SPE (Specifity) and OA (Overall Accuracy).

As a further experimental analysis, we wanted to test the methodology also on images of a different type than Sentinel-2 ones. In this regard, we report the results deriving from the application of the methodology respectively on a Landsat image (Figure 8) and IKONOS image (Figure 9) through object- and pixel-based methodologies of remote sensing image classification. In this regard, Figure 8 shows the segmentation/classification of Landsat data relating to the territory of the municipality of Melito di

| METHOD | ERROR% | Type 1 and 2 errors from the Error Matrix |
|---|---|---|
| Object based/Pixel based | 1.17 | 20% |
| Traditional Neural Network | 2.11 | 31% |
| SNN (RSI-CB128) | 1.3 | 23% |

Figure 7: Performance evaluation of different methodologies on Sentinel-2 images.

Porto Salvo (in the province of Reggio Calabria, Italy), where 5 classes are highlighted (Impervious surfaces, Water, Agriculture, Rural and Sub-rural) through a pixel based classification. Figure 9 shows an image of tha same area of the territory of the municipality of Melito di Porto Salvo, in the province of Reggio Calabria, on which a multi-resolution segmentation and subsequent object-based classification was carried out, with a level of segmentation applied on the bands blue, green, red and nir from the IKONOS dataset.

Figure 8: Classification of Landsat data: Melito P.S. (RC - Italy).

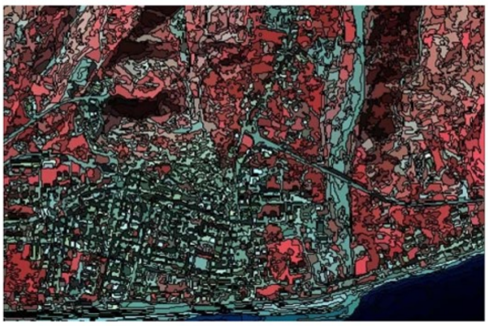

Figure 9: Segmentation level I applied to the IKONOS dataset.

By comparing (in terms of average values) the results obtained from the application of the proposed methodology with those deriving from the segmentation/classification methodologies reported above, also in this case the goodness of the SNN methodology (RSI-CB128) is highlighted in terms of accuracy and shorter processing times by comparison with the methodologies known in the literature (obviously the expected results are better for the IKONOS images only and worse for the Landsat images).

From both table in Figure 7 and Figure 10, it can be seen that the advantage of the proposed method SNN (RSI-CB128) is particularly evident in the use of Sentinel-2 images, shows good results

| METHOD | ERROR% | Type 1 and 2 errors from the Error Matrix |
|---|---|---|
| Object based/Pixel based | 1.1 | 21% |
| Traditional Neural Network | 2.16 | 32% |
| SNN (RSI-CB128) | 1.94 | 27% |

Figure 10: Performance evaluation of the different methodologies on Landsat and IKONOS images.

with IKONOS, while for images Landsat the method is not particularly performing.

## 4. CONCLUSION

The Copernicus project and the Sentinel data are of utmost importance today, especially with regard to the continuous monitoring of the ground in order to preserve cultural and environmental assets (Addabbo, Focareta, Marcuccio, Votto & Ullo, 2016). In this way, we created both warning and long-term prevention systems. Amongst the many features of the project, this is made particularly true by the planned mode of access to the data, which allows a multitude of organizations and associations with limited budgets to be able to carry out effective analyses by taking advantage of their information content.
On the other hand, the resolution available today could result in the need to use expensive proprietary software to achieve effective classifications. In this work, the use of SNN - SELUs Classifiers trained on public datasets with high spatial resolution was proposed for use on Sentinel data. This investigation led to positive results in terms of both training time and classification error. It should be noted that these first experiments will be verified with other processing carried out on other images and larger datasets. Some possible future developments for image classification using SNNs include:

- Improving computational efficiency: Since SNNs require more processing time compared to other machine learning techniques, improving the computational efficiency of SNNs could enable faster and more accurate image processing.
- Integration of multiple data: Using multiple data, such as images at different spatial and temporal resolutions, could improve the accuracy of classification using SNNs.
- Development of specific pre-processing algorithms: Designing specific pre-processing algorithms for images could improve the accuracy of classification using SNNs.
- Improving learning capabilities: SNNs could be further developed to improve their ability to learn from complex data and adapt to environmental variations.

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