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Deep learning technique for image satellite processing

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ABSTRACT

Recently, several technological solutions based on deep learning have been developed for the processing of multispectral satellite images. These solutions have broadened the scope of spatial remote sensing and further explored the earth and space by avoiding human efforts in heavy manual tasks. However, even though this progress gives even better performance it is difficult to design an efficient deep-learning pipeline for satellite image processing in the absence of a well-developed standard. Thus, we propose a new framework to design and implement a machine-learning model for satellite image processing through a set of machine-learning methods in the form of a protocol adapted to the context of space imagery. The choice of the dataset adapted metrics, exploitation of the product format, data enrichment, spatiotemporal indexing and analysis, contrast enhancement and noise reduction/suppression, network parameterization, model scalability, data normalization, spectral dependency, and processing complexity reduction are among the methods adapted to the processing of multispectral satellite images by deep learning. All these methods are analyzed in depth in order to understand their usefulness and their contribution to the performance of learning models before testing them on real use cases. This method constitutes the first standard framework for the use of deep learning in the processing of multispectral satellite images.

1. INTRODUCTION

The use of satellite images today in GIS is an important part of the analysis and processing of spatial remote sensing data [1]. The use of satellite images in machine learning models in the context of computer vision is a rapidly expanding field including environmental monitoring [2], change detection [3], semantic segmentation [3], super-resolution [4], registration [5], fusion [6] and object classification [7]. Experience has shown that deep learning methods have now surpassed all traditional methods in all these areas.

Moreover, the processing of multispectral satellite images requires an understanding of the specificities of these images which differ from ordinary images by several characteristics, in particular the size and depth of these images (number of channels or bands) which requires an adapted coding. However, we do not have today a standard for the processing of this type of image to exploit the work done in other areas of application.

This work aims to implement a methodology of artificial intelligence (particularly deep learning) for the processing of multispectral satellite images within a process of machine learning, allowing to have added value in spatial remote sensing. This study aims to make available to the public all the methods necessary for a good mastery of deep learning for spatial imagery. This methodology is valid for several machine learning architectures such as CNN [8], GAN [9], AE [10], RNN [11], and other categories of learning models.

This paper is organized as follows. The first section deals with the state of the art and related work in this field of machine learning. The second section focuses on the methodology proposed in this paper for the processing of multispectral spatial imagery. Finally, the last section concludes this work and proposes some perspectives for future work.

2. Background and related works

A satellite image is a raster matrix in pixel form that stores data related to remote sensing, i.e., the values of electromagnetic energy captured by the airborne sensor on the satellite. Thus, figure 1 represents a satellite image with a zoom in order to visualize the pixel layout.

The size of the pixel represents a delimited area of the earth's surface which determines the spatial resolution of the image (the size of the small object visualized in the image). In addition, each pixel has a precise location on the earth's surface (georeferencing [12]) which represents

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its geometric property, and its value represents its radiometric property.

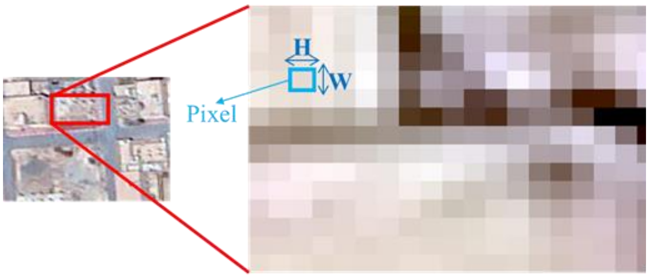

Figure 1. Representation of an image in pixels of size H*W (H is the height and W is the identical width)

Each pixel on the matrix represents the brightness and color of this point on the earth's surface. The process of acquiring satellite images consists of using an airborne sensor on an artificial satellite orbiting in space, measuring the amount of sunlight reflected by the object on earth according to the diagram in Figure 2.

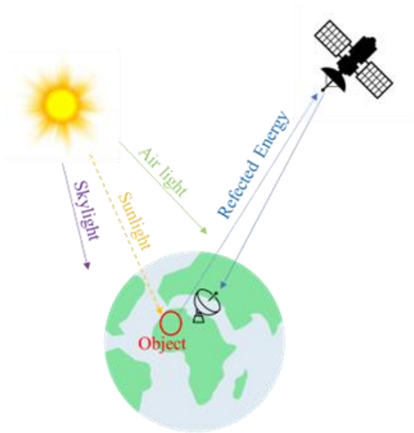

Figure 2. Process of acquisition of a satellite image by an optical sensor

Remote sensing allows the exploitation of reflectance values (pixel values) on satellite images to analyze various domains such as change detection, land monitoring (urban planning trends, ...), and vegetation analysis (cover, health, ...).

Satellite imagery is characterized mainly by its size (depending on the spatial resolution) and its definition (depending on its spectral resolution) producing voluminous images.

A satellite image has one (panchromatic) or more spectral bands (multispectral) and each band is characterized by its wavelength on the electromagnetic spectrum as described in Figure 3.

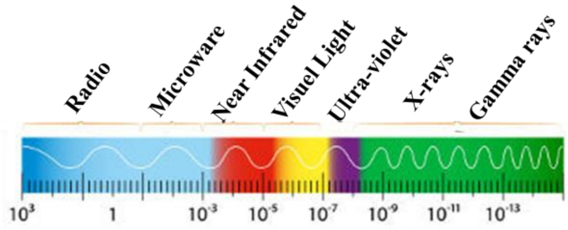

Figure 3. Electromagnetic spectrum of spectral bands and corresponding wavelengths

The separation of light and color according to wavelength is done through corresponding filters. The use of filters allows either to visualization of an image in a colored composition (Figure 4) or a false color composition to see phenomena not visible to the human eye. Thus Figure 4 represents a satellite image in true color composition at the top and the corresponding image in false color composition at the bottom.

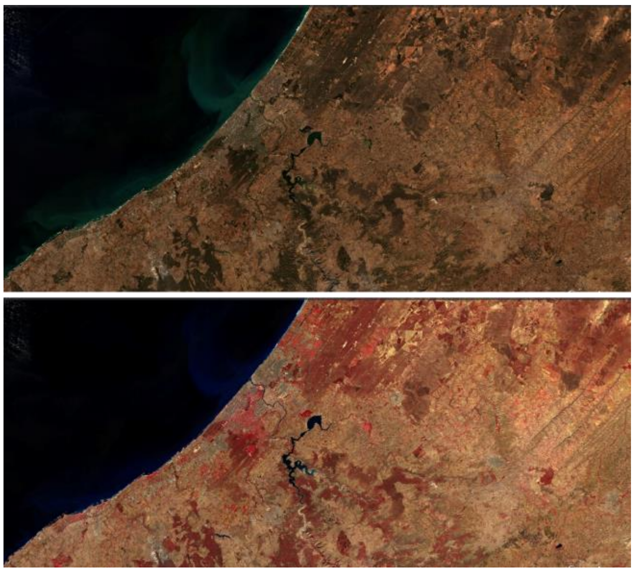

Figure 4. Visualization of a satellite image of the city of Rabat with 2 different color compositions

A satellite image is produced with metadata related to the acquisition conditions and sensor characteristics such as spatial resolution, acquisition date, georeferencing, and cloud cover. This data is required for processing and management within an artificial intelligence pipeline applied to satellite images.

The state of the art of works done on multispectral satellite images concerns each isolated application domain with proposals of adapted models. Thus [4,13-17] have worked on super-resolution, [18-27] have addressed detection and classification, [28] have worked on segmentation, moreover [7] have addressed the field of the scene and object classification, [3] have worked on change detection, without forgetting [29] which have proposed a processing framework for LULC. However, we also mention a benchmark of the state of the art of existing models made by [30], and finally the systematic study made by [31].

3. Methodology

Our method consists in using a set of procedures well elaborated and adapted to the context of space imagery allowing to have relevant information extracted in spectral bands of satellite images by respecting a standardized scientific procedure. This method exploits the technological progress in deep learning. This procedure constitutes a standard for the use of satellite imagery with deep learning, but it must be adapted according to the objective to be reached. This method proceeded by a systematic analysis of all the works of deep learning for the processing of multispectral satellite images to have relevant conclusions allowing to have the whole of these techniques which constitutes a framework for the design and the implementation of adapted learning models.

3.1. Scalability of the model

In the beginning, the model is trained and tested on a restricted area on which we have satellite data and we prove the model on this part of the land surface, so we must go through production by the generalization of the model to calibrate and validate the algorithm by an adaptation and enrichment of the model by other data for a better reproducibility at the largest scale of the territory.

The choice of the dataset allows a better generalization of the model but also, but we must validate our model with data across the world for better reproducibility (a model trained in central Morocco (where we have areas with a large urban concentration) is not reproducible on the south of Morocco (where we have desert areas).

Indeed, the characteristics of the land cover vary globally to a high degree, a model trained on images of forest areas in the Moroccan Rif (the cedar grove) may fail when applied to images of forests in the southwest (the argan grove), for example.

Moreover, the data must be spread out over the year to have the climates over the year. It is also necessary to have different targets on the ground (buildings, land, sand, ...).

3.2. Data normalization

The variation in the scale of the spectral bands of the satellite image requires normalization to reduce the scale factor. As the divergence of the wave intervals of the spectral bands leads to a covariance shift within the model adapted by non-uniform distributions on the hidden layers, this variation can also lead to a non-convergence of the network or poor learning of the objective function of the algorithm. For this reason, it is proposed in this protocol to use a batch normalization [32] to have the data of the spectral bands within the interval [0,1], as well as proceeding to the training of each spectral band on the network, which keeps the initial distribution and reduces the spectral divergence.

Atmospheric compensation can also be used to normalize the spectral data, giving normalized reflectance values for each pixel in each spectral band.

3.3. Spectral dependence

The consideration of the spectral dependence between the bands of the satellite image allows to exploit of the correlation due to the overlap between the wavelengths on the electromagnetic spectrum in order to eliminate the redundant information on the channels of the image which reduces the parameters of the network, this consideration allows solving the problem of variance within the spectral bands in a learnable and efficient way. The consideration of the inter-spectral dependence allows to an increase the performance of the network and improves the speed of inference [33].

3.4. Reducing processing complexity

The consequent size of the satellite image and the depth of the spectrum give rise to problems of storage and processing of the images as well as the complexity of the neural network and its inference. Therefore, it is necessary to process the satellite image by an adapted method to reduce the amount of information transmitted within the model pipeline. This problem influences the convergence of the network and its performance in addition to having a powerful infrastructure.

Indeed, for the processing of ISM by deep learning, it is necessary to choose a network with a reduced number of parameters which reduces the computation required for the processing performed by the model. As specified in the particularities of ISM, each observation contains large amounts of data. As such, we must exploit all the neural network techniques that allow us to lighten the network and increase its inference speed.

3.5. Network parameterization

The learning model on ISM must be the most reliable not to alter the information on the image; indeed, it is necessary to keep the realistic character of the satellite images after the passage by the processing pipeline by keeping the fine textures and the realistic details on the produced image. Moreover, the consideration of the dependency between the intermediate layers by learning the correlations of the internal characteristics allows for controlling the information in an integrated way.

If we exploit an existing model that works on ordinary images, we must redefine its parameters and take into consideration the optimization and acceleration techniques of neural networks so that it processes satellite images efficiently and optimally.

If we use a processing process upstream of the network (such as interpolation for example) or downstream (such as noise removal) we must integrate it into the network so that the latter can learn efficiently according to the input image, as experience has shown that the operations performed by neural networks in learning are even better than the traditional operations in order not to lose the sense of detail.

Thus, we must use a process of dimensionality reduction in the input of the network in order to control the input and give the model the ability to learn better. Indeed, depending on the learning architecture used for the processing of ISMs, the best dimensionality reduction strategy is adopted. For example, if CNN networks are used, smaller convolution kernels must be used to identify the vector of important features of the satellite images with a better inference time. Moreover, mosaicking as an additional phase allows for reducing the dimensionality.

On the other hand, ISMs usually have more than 3 spectral bands, so it is necessary to work with a network that manages all the channels of the input image; thus, no spectral band should be canceled, such that not considering a band cancels the information contained in it.

In addition, a thorough analysis must be made in order to have an adequate balance between the number of network layers and the objective to be reached to have the level of abstraction allowing the best precision, taking into consideration that time takes precedence for the case of ISM. Indeed, if we work with CNN networks it is necessary to have more filters in order to detect more features such as the features of the satellite images being even more numerous and finer, to master the input image.

Thus, other techniques must be taken into consideration, among others:

Use of neural network acceleration methods in order to gain speed of inference, such as working with the network technique [34].

Do not lose sight of the objective of increasing performance with better network stability.

Depending on the objective to be reached and the architecture used, the multi-scale fusion technique [35] can be considered in order to keep the maximum amount of information.

If we manage to work with parallel networks, we gain enormously in the learning time of the network and its predictive capacities.

The transfer of internal parameters of the network for fast convergence of the model (the transfer of filters for example within the CNN networks).

In addition, we experimented in the context of the super-resolution of ISM (Image Sentinel-2) to prove the effect of convolution within a CNN network. Indeed, with a spatial resolution of 10 to 60m and 13 spectral bands and knowing that the Sentinel-2 tiles are image products of 100*100km so we will have an image of (10^4X10^4X13) pixels so for a convolutional layer trained on this image will require 2.3x1012 multiplications to be done for a single convolution layer for a filter of 196.

NM/P= Kernel width X Kernel height X Number of channels X Number of kernels X Number of vertical slides X Number of horizontal slides =3X3X13X196X10^4X10^4=2.3X10^{12}.

On the other hand, we can use convolutive layers separated in depth. We will have 104X104 individual convolution so in total 9 x10^{10}. This proves the use of convolutions separated in depth within our neural network.

3.6. Contrast improvement and noise reduction/removal

The satellite image contains at the beginning generally little contrast by the fact that some bands use the entire range of the acquisition sensor, so we can find in extreme cases (snow at the top of the Atlas Mountains, or the black basalt plateau of Azrou or Timhdite), so we will resort to the equalization of the histogram to stretch the reflectance values on the total capacity of detection of the display screen.

In addition, we can improve the contrast of the dataset in input, if this operation does not influence the objective to be achieved, before launching the learning process by determining the important areas within the image on each spectral band.

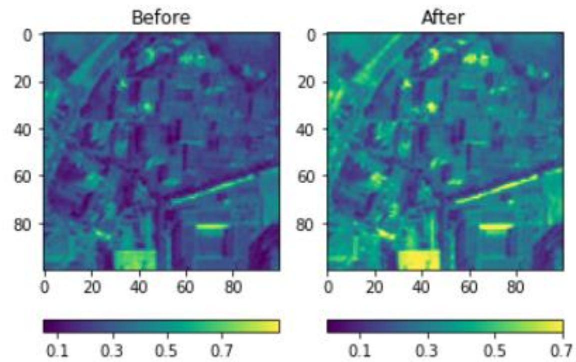

Figure 5. Improvement of the contrast of an image in input to the neural network

This improvement can be done by several approaches as in the case of [36] which uses the DWT technique to decompose the satellite image into spectral sub-bands; or by using swarm intelligence as in the case of [37] otherwise, we can use the DTCWT transformation based on wavelets as for [38].

However, this improvement can be combined with filtering (e.g., frequency filtering) and noise reduction which mainly involves the removal of clouds and atmospheric contaminants, through progressive learning integrated with the neural network exploiting the satellite imagery without altering the spectral information on the image.

3.7. Spatio-temporal indexing and analysis

Indexing is an effective technique for processing large-scale data such as the case of ISM, in fact, depending on the architecture and the framework used, we can benefit from the power of this technique by using distributed clusters with indexing with the inference time and space, i.e., the geographical position of the pixels to be processed using spatial indexes.

This technique consists in ensuring that values close to each other in the multidimensional space of spectral bands are physically stored in close memory bins within the storage space for processing, which reduces the learning curve of the adopted model.

Indexing allows for better management and optimization of the network with even better time by facilitating access to spatial information.

3.8. Data Enrichment

The enrichment of the ISM data allows to have an efficient model with better scaling, we can proceed to several techniques to achieve this goal. One of the effective methods in the context of deep learning is data augmentation to expand the learning scope. However, this technique must be used with care for the case of ISMs in order not to alter the information and therefore have an unusable model. Indeed, since the performance of the deep learning model increases with the training data, this technique can contribute to the diversity within the data by adding new ISMs. However, an experiment was performed in order to see the effect of each transformation on our dataset, while keeping the fidelity of the ISM and its informational integrity. This choice was made after several experiments by measuring the contribution of the transformations to the gain in performances generated after transformation by data augmentation. Moreover, these transformations must achieve the best balance between the spatial invariance generated by the data augmentation and the spatial dependence imposed by the georeferencing of the ISM.

For the horizontal and vertical shifts, we can use a 10%-pixel transformation with a uniform fill.

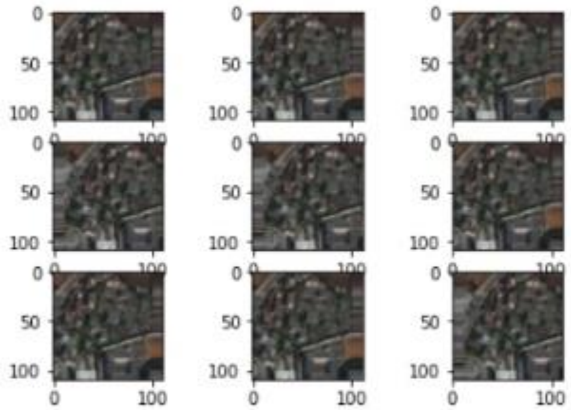

Figure 6. Data-Augmentation of horizontal and vertical shift (width_shift_range= [-10,10])

The vertical and horizontal shift for ISMs breaks the strong coupling between the image and its shooting angle. As the flip determines the angle of view that significantly influences the model.

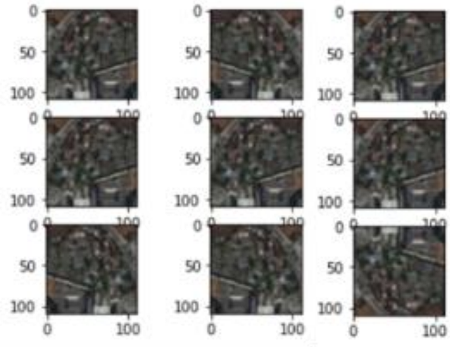

Figure 7. Data-Augmentation of the flip (horizontal_flip=True; vertical_flip=True)

Different angles can be used for the rotation angle depending on the objective to be achieved. However, if we consider the treatment within a mosaic, it is necessary to use the same rotation for all the mages constituting the mosaic in order not to alter the integrity of the information of the ISM.

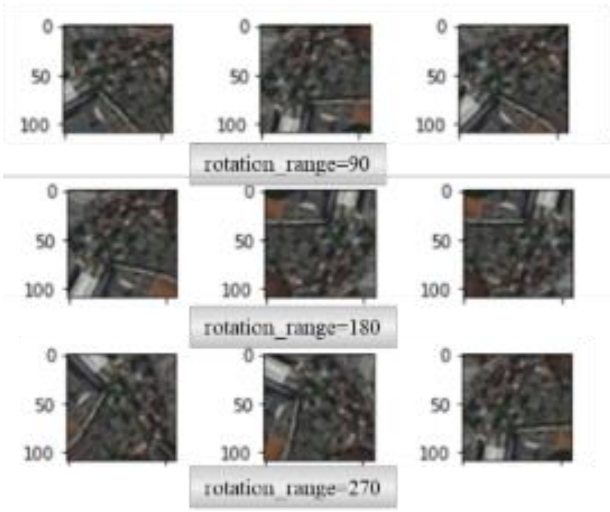

Figure 8. Data-Augmentation of the rotation (rotation_range=90;180 ;270)

We can apply both lighting and shading. In order to break the coupling with the shooting time and the atmospheric conditions that can influence the learning capabilities of our model, so we apply a random increase of the brightness from 10 to 20% on the training dataset.

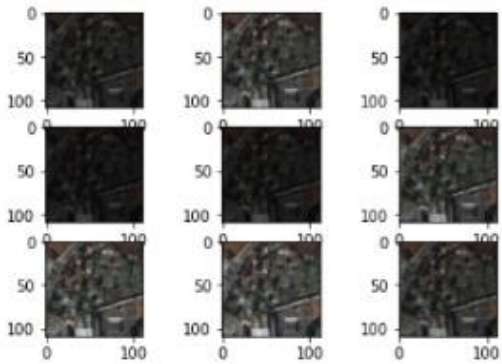

Figure 9. Data-Augmentation of brightness (brightness_range = [0.2,1.2])

Transfer learning [7] and active learning [39] can also be used to enrich the data.

3.9. Exploiting the product format

Each satellite image is delivered according to a process determined by the image suppliers; indeed, one of the very interesting formats for the case of ISM is the mosaic format. Indeed, if the product is delivered in mosaic format, we can directly exploit this functionality, otherwise, we can proceed with a tool adapted to the creation of mosaics from a global ISM. Thus, working with small mosaics allows a great efficiency of the neural network.

This mosaicking technique greatly helps to solve the problem related to the large size of the ISM and the difficulty of processing ISMs with several resolutions within the spectral bands, by dividing the ISM into several image partitions taking into consideration their spatial positions.

This functionality in the form of a virtual layer is combined with the metadata query part of the images within the network to propagate the data on the pipeline taking into account their spatial positions as we know the geographical position of each pixel of the image; thus, the mosaic allows to query the tiles as if we were interrogating the original image. The mosaic also manages the difference in spatial resolution within the spectral bands of the same satellite image. This feature also allows the reconstruction of the global image at the end of the network.

The movement within the mosaic must be done with a one-pixel step to inspect the edges of the image in the same way as the center.

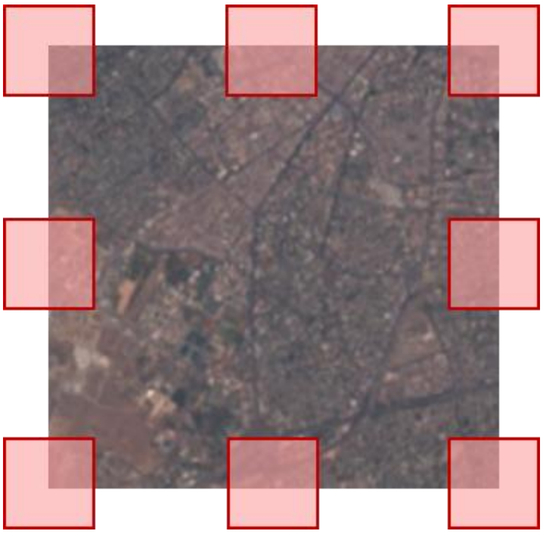

Figure 10. Positions impossible without padding consideration

This consideration allows not to the loss of the spatial dimension on the satellite images.

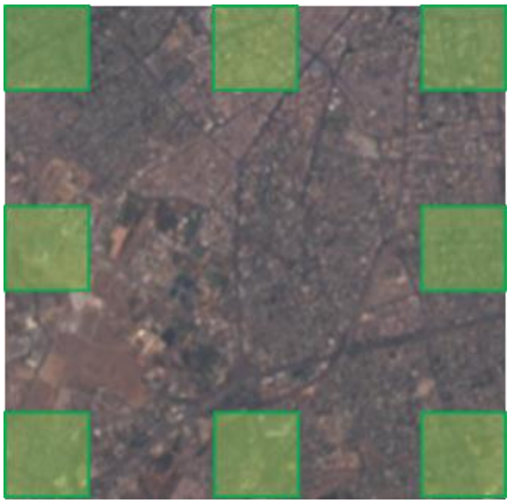

Figure 11. Image edge inspection using mosaic padding

Experience has shown that the use of this method improves the network performance considerably while preserving the distribution of our satellite images on the edges [33].

If we consider the mosaic format, the size of the training batch must be the same as the size of the mosaic images to have efficient training, and if we consider the increase of the data, we must have the same transformations on the same training batch.

3.10. Adapted metrics

To measure the efficiency of the models, we note that most of the models use standard metrics to measure the performance of neural networks for processing satellite images, however, the metrics applied on ordinary images are not always reproducible on satellite images, so we go through a benchmark and a detailed study on the metrics to have better results.

3.11. Choice of the dataset

The choice of the dataset for training the model is interesting for any machine learning model, which takes more importance in the case of satellite images where the spatial reference is important. This choice must take into account the environmental and natural diversities of the area under study (taking aquatic, desert, forest, and mountain images), the richness of the area (areas with interesting details -with a better urban concentration-) of the time of taking the image (images taken throughout the year on the 4 seasons and images taken throughout the day). This choice allows for solving the problem of spatial and temporal invariance.

4. Conclusion and perspectives

This study was motivated by the lack of a standard for the processing of multispectral satellite images by deep learning. This research work constitutes a systematic study in the form of a standard for the processing of multispectral satellite images by deep learning. This study proposes a set of methods and proposals to follow for a better design to have efficient machine learning models with new performances using spatial imagery. This protocol takes into consideration all the characteristics of satellite images and deep learning to see reliable models.

However, further research is needed to develop a satellite image processing method for each application domain depending on the objective to be achieved by the machine learning model.

Author's Note

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