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A Deep Learning model for identifying mountain summits in Digital Elevation Model data

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***Abstract*—Analyzing Digital Elevation Model (DEM) data to identify and classify landforms is an important task, which can contribute to improve the availability and quality of public open source cartography and to develop novel applications for tourism and environment monitoring. In the literature, several heuristic algorithms are documented for identifying the features of mountain regions, most notably the coordinate of summits. All these algorithms depend on parameters, which are manually set. In this paper, we explore the use of Deep Learning methods to train a model capable of identifying mountain summits, which learns from a gold standard data set containing the coordinates of peaks in a region. The model has been trained and tested with Switzerland DEM and peak data.**

***Index Terms*—Mountains, DEM, Deep Learning, Landforms mapping**

I. Introduction

Landforms are natural features of the landscape, such as mountains, hills, plateaus, canyons, etc, which characterize the Earth surface. Their identification and classification are essential for geomorphological mapping [8], a problem of interest for a wide spectrum of Earth sciences such as hydrology, morphometry, morphology, glaciology and urban planning. Landforms mapping was historically performed by direct observation in the field or by using topographic maps; recently, with the advances in digital imagery, Digital Elevation Models (DEMs) have become the most adopted tool for analyzing the Earth surface [34]. DEMs are 3D representations of the Earth, derived from different sources, such as Laser Imaging Detection and Ranging (LiDAR) or Shuttle Radar Topography Mission (SRTM) campaigns [9]; DEM data form a matrix in which each value represents the altitude of a point on the Earth. Thanks to different visualization techniques, DEMs are useful to study a surface area from different viewpoints and at different scales. Several works designed methods to extract landforms from DEMs [32] [22] [16]. In particular, mountains and mountain peaks identification are a sub-problem of landforms detection, which we address in this paper. The problem can be defined as follows: *given the DEM representation of an area of the Earth surface, identify the coordinates of the points that belong to a mountain landform.* A further restriction of the mountain landform identification problem is *summit identification*, which processes DEM data to determine the coordinates of a single point that represents the summit of the mountain.

Mountain area and summit identification have important applications. The identification of mountain slopes can be used to analyze hydrogeological and landslide risk and to monitor climate change or anthropic effects [5], such as reduction of glacier and snow coverage, which are fundamental for water supply in many regions of the world [10]. Mountain summit identification can support the improvement of Voluntary Geographical Information Systems (VGIS). Such systems, e.g., the popular Open Street Map (OSM), depend on the contribution of volunteers to provide information of geographical entities, including mountain peaks, which challenges the quality and quantity of data available. For example, at the moment, OSM contains $\approx 506,097$ mountain peaks, of which 36,25% miss the altitude value. Therefore, automatically extracting candidate mountain summits, with their coordinates and altitude, and using the volunteer contribution to validate and augment such data set can be a formidable tool to boost the quality and quantity of geographical information in a VGIS.

The identification of mountain areas, and thus also of mountain summits, depend on the definition of mountain, which is an ambiguous concept [11], [12]. Different works have used alternative features to characterize mountains for different purposes; for example, [15] classifies mountains as minor, submajor and major, according to three geographic parameters: local relief, elevation and prominence. Other features, such as isolation, slope, curvature, have been employed too. A common trait of mountain characterization methods is that they depend on parameters that the user has to configure, to decide if a given point can be considered part of a mountain. The selection of parameters values to obtain the most accurate identification is a complex task, especially when multiple parameters are involved.

In this work, we explore Deep Learning (DL) [23] as an alternative to the manual selection of parameters in heuristic algorithms. The idea is to let a deep neural network to learn the optimal parameter configuration for recognizing mountain summits, by training it on a suitable gold standard. To this purpose, we exploit existing digital cartography, where the coordinates of (selected) mountain peaks are reported. Traditional maps, and their digital counterparts, embody significant

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knowledge and tradition on the localization of mountain summits and can thus be used to train a DL classifier, which could apply such knowledge to identify peaks not present in the traditional cartography or peaks in different areas, for which public cartography is unavailable or less complete. The input to the DL model is a DEM data set, appropriately encoded, and the output is a probability map of locations to represent a mountain summit; such output can be used in two ways: to identify peaks not represented in the available cartography and to estimate (thanks to the DEM elevation data) the altitude of peaks that miss such information in a GIS.

The proposed DL method is exploited in a crowdsourcing platform whereby volunteers can validate novel discovered peaks and the altitude of already known peaks, before injecting the information into a VGIS.

The contribution of this paper can be described as follows:

- We formulate the mountain summit identification task as a learning problem, in which a DL model is trained by supplying to it the DEM data of a region and a set of ground truth peak summit coordinates in the same area.
- We experiment such methods in a mountainous region in Switzerland, using SRTM data at one degree resolution as input and peak coordinates from the OpenStreetMap (OSM) and SwissNames3D public data sets as gold standard.
- We evaluate the performance of the DL model, based on a distance-based, heuristic peak comparison function, and discuss the possible directions of improvement of the proposed approach.

II. Related Work

A. Mountain peaks extraction from DEM

Heuristic methods for mountain detection have been studied as a subproblem of landforms mapping. In the pioneering work [11], the authors point out that a portion of terrain can be mapped to different landforms, depending on the scale employed to analyze it. Therefore, an area may contain various landforms in different degrees, which calls for the application of fuzzy set theory to terrain analysis. In [12] this hypothesis is embodied into a method that computes the fuzzy membership of each DEM pixel to 6 different morphometric classes: Pass, Pit, Plane, Ridge, Channel and Peak, obtained through the evaluation at several scales. At each scale, the Boolean membership of the pixel to each class is computed using the terrain slope and curvature as features and then a compound multi-scale fuzzy value is calculated. The method is implemented in the Landserf[1] application [35]. The work in [13] presents the qualitative results of applying the described method in two different territories. Landserf contains another heuristic method to find peaks, based on the assumption that a summit is a location surrounded by other points lower by a given amount. The method requires two parameters: the minimum height for a point to be a candidate peak and the minimum elevation difference w.r.t. the neighbors [35].

Other studies focused on analyzing the shape of a peak relative to its neighbors. [7] considers mountains peaks as fuzzy entities and defines a multi-scale peaks extraction algorithm, similar to [12], based on local properties such as relief, mean slope, relative altitude and number of summits in the neighborhood, plus topographic position and context. The result is a value, representing the peak class membership of a point, that can be thresholded to delineate a peak boundary. The author of [28] and [29] combines topographic and morphologic criteria: a point, to be considered a peak, must be the highest within its 8 neighbors (3x3 window), must reside in a non-flat area and must have at least a certain horizontal and vertical distance from other candidate peaks. The same author, in [30], studies in detail the shape of a peak. The results show that shapes are dependent on each other and not universal.

In [20] the authors map landforms, including peaks, with pattern recognition. They introduce Geomorphons (geomorphologic phenotypes) and identify 498 of them using Local Ternary Patterns (lookup distance and a flatness threshold are required parameters) using the line-of-sight principle. By performing a generalization of the different patterns to the ten most common landforms, a classification of the terrain is achieved.

In [21] the authors present another heuristic approach to calculate prominence and isolation of the mountains. Isolation is computed by searching the minimum distance from a peak with higher elevation; prominence is determined by finding the minimum vertical distance needed to descend from the peak and climb to a higher peak. Both indicators are exploited to calculate the prominence and isolation of every peak in the world, and the most prominent and isolated peaks missing in the PeakBagger[2] dataset are identified.

B. Deep Learning on GIS

Artificial Intelligence and Deep Learning algorithms have proved capable to achieve high quality results in a wide range of Computer Vision tasks, such as image classification, detection, localization and segmentation [18].

Recently, several works on geoscience and remote sensing have addressed the analysis of aerial images by using Convolutional Neural Networks [36]. In particular, Fully Convolutional Neural Networks [25] have been applied for aerial images segmentation, tackling land cover and objects mapping [2] [27], in which each pixel is assigned to a given class (e.g. vegetation, building, road, car, etc). Artificial Intelligence has also been exploited for DEM data analysis. Marmanis et al. [26] proposed the classification of above-ground objects in urban environments by using a Multilayer Perceptron model. In [19] the authors proposed a DL method to digital terrain model (DTM) extraction from Airborne laser scanning (ALS) point cloud data. Their approach maps the relative height difference of each point with respect to its neighbors, in a square window, to an image. This way the classification of a point is treated as the classification of an image, resulting in

[1] http://www.landserf.org/

[2] http://www.peakbagger.com/

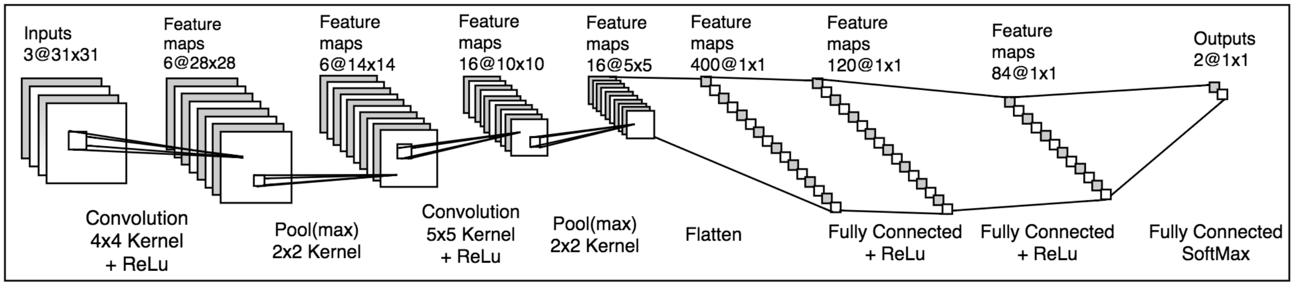

Fig. 1. CNN architecture

low error rate in detecting ground and non-ground points. This method conserves well the terrain features even in mountains, which is our case of interest.

Other related studies comprise diverse techniques to cope with the lack of high resolution DEM coverage in many areas of the Earth, such as super resolution of DEM [4] and synthetic generation of terrain images, essential for supervised learning tasks, which can been addressed through Deep Generative Adversarial Neural Networks (GANs) [17] [3].

Our work aims at applying Deep Learning techniques, so far only employed to detect local scale above ground objects or urban terrain features, for global scale peak summit identification. In doing so, we explore supervised learning to learn classifier parameters and reduce the need of manual parameter selection, typical of current heuristic methods.

III. Peaks extraction from DEM using DL

The goal of this work is to explore the application of Deep Learning techniques for the extraction of landforms from DEM data, with specific focus on mountain summit identification. For this task, we exploit Convolutional Neural Networks (CNNs), a deep network architecture extensively used for the recognition of patterns in images. CNNs operate directly on pixel images and can recognize a wide spectrum of patterns. CNNs can be fruitfully applied to the mountain summit recognition from DEM data for the following reasons:

- They work on input images divided in sub-regions repeatedly processed by the convolution step. This is analogous to striding across the DEM of a region with a sliding bi-dimensional window to process the altitude data.
- They can analyze arbitrary pixel-level information and discover complex spatial relations. In our domain, pixel-level information encodes the features that can be extracted from the DEM, which may support the identification of a peak. In this paper, we use three features for summit identification: *altitude*, *curvature* and *slope*.
- They map each input pixel into an index value for each predicted class; the index ranges between 0 and 1, the sum across classes adds up to 1 and each value can be interpreted as the likelihood that the pixel belongs to the class. In our case, this is analogous to computing the likelihood that an area of the Earth surface is a mountain summit or not.

Specifically, we adapted a LeNet model [24], with the architecture shown in Figure 1; the original architecture is modified to match the CNN input to the encoding of the DEM data (31x31x3 inputs are used instead of the usual 28x28 gray-scaled inputs); the center pixel of the input image is mapped to one of the two classes: mountain summit / non mountain summit.

Input data. This work uses as input the Shuttle Radar Topography Mission (SRTM) DEM provided by NASA [9]. DEM data is organized into a regular grid, with resolution variable between 1 and 3 arc-seconds, depending on the region of the Earth; each grid point is associated with the altitude of the terrain in that position.

We focused on the Switzerland territory, where the SRTM DEM is available at 1 arc-second resolution (SRTM1), which corresponds to $\approx$ 30m in areas relatively far from the poles. STRM1 DEM data are divided into a series of tiles of 3601x3601 pixels; an intuitive way of visualizing them in the 2D space is as gray scale aerial images, where the color of every pixel denotes the height of the terrain in that area. Figure 2 shows an example. Each DEM tile spans 1 degree in

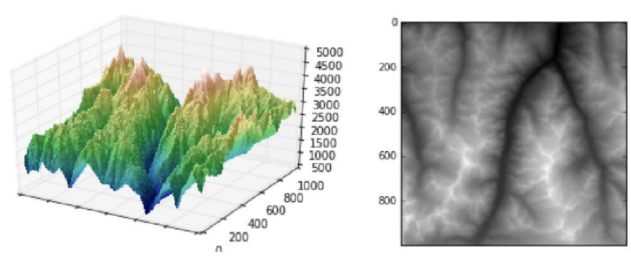

Fig. 2. 3D and 2D DEM visualization

latitude and in longitude; for example, the tile N46E007 stores the elevations of the Earth between 46° and 47° latitude and 7° and 8° longitude, organized into a grid. To account for the curvature of the Earth, we rescaled the DEM files, so that each rescaled pixel represents a square area with the same extension in both directions[3].

[3]Note that the distance from 46° to 47° $\approx$ 111.19 km, whereas from 7° to 8° is $\approx$ 77.24 km; therefore the original tile is rectangular and not squared. Thus, the normalization.

To train the CNN three features are considered: (1) elevation, read directly from the DEM, (2) the slope, calculated from the DEM, which ranges from $0°$ to $90°$ and (3) the curvature of the terrain, also calculated from the DEM, whose values can be negative, for a convex surface, or positive, for a concave surface. To reduce noise in the raw input data, feature values are normalized between -1 and 1, with -1 denoting the minimum feature value and +1 the maximum.

Ground Truth. The goal of this work is to build a model capable of learning the location of mountain summits, to help enriching the content of VGIS with more information about peaks and their altitude. Selecting a gold standard to train the model is of prominent importance; this amounts to identifying a geographic region for which the peaks and the coordinates of their summit are known exactly. Such an ideal gold standard is impossible to build in practice: on one side, also professional cartography makes a selection of which peaks to show, for reasons of prominence, tradition, culture, and readability of the map; on the other side, public data sets are mostly built by volunteers and cannot be assumed to be 100% complete and precise. The noise in the ground truth must be taken into account when evaluating the model output, because accuracy may be undermined, e.g, due to the fact that a false positive (i.e., an apparently wrongly identified peak) may indeed correspond to a peak that exists in reality but is not registered in the available cartography. The implementation of techniques for coping with label noise [14] is part of our future work.

As a reasonably good ground truth for training the CNN, we have built the gold standard by merging two different public available databases of named mountain peaks: OpenStreetMap (OSM)[4] and SwissNames3D[5]. The resulting ground truth data set contains 12,788 peaks, distributed as shown in Figure 3.

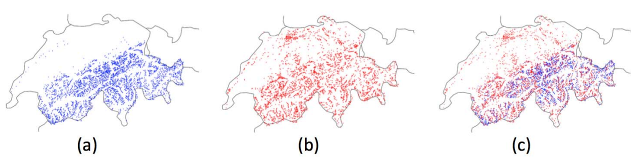

Fig. 3. Moutain peaks distribution in (a) SwissNames3D and (b) Open Street Map (c) their combination

Based on the ground truth, a DEM pixel is considered *positive* if the area it covers contains the coordinates of one ground truth mountain summit, *negative* otherwise.

Patches generation. The training and validation datasets were built extracting 31x31x3 patches from the regions shown in Figure 4. Each patch is a square of 31x31 pixels, which represents a physical region of $\approx 957\text{x}957$ meters; each patch is also associated with the values of altitude, slope and mean curvature in the region represented by the patch. A patch is *positive* if its center pixel is positive, *negative* otherwise. One positive patch is extracted for each peak in the ground truth dataset, using the corresponding coordinates as the center pixel of the patch. Different heuristics were also applied to the positive patches, in particular, the one that proved to perform better was to create also positive patches for the 8 direct neighbors of the positive pixel. The same number of negatives are generated, by sampling randomly other points in the grid.

[4]https://www.openstreetmap.org

[5]https://shop.swisstopo.admin.ch/en/products/landscape/names3D

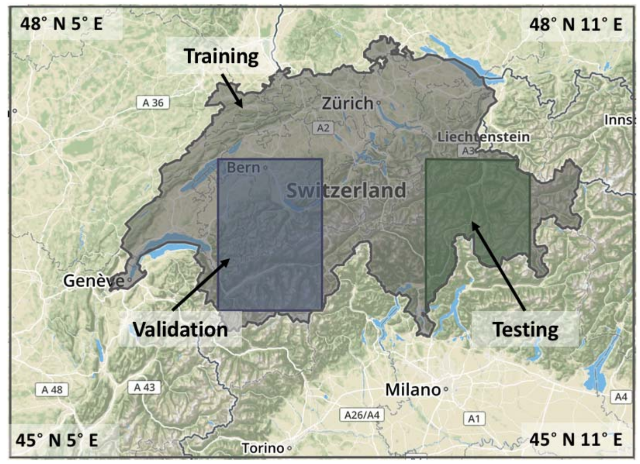

Fig. 4. Territory distribution for the datasets.

Post processing. The CNN model is fed with the rescaled DEM tiles of the region of interest and outputs a matrix of the same dimensions as the input, in which each pixel is associated with a value that denotes its probability of containing a summit. Extracting peak coordinates with a simple filter on the output value proved inadequate, because cluster of neighboring pixels tend to be assigned to the same class and considering each positive pixel independently could lead to the inference of multiple close-by, yet distinct, peaks. Therefore, we developed a post-processing algorithm that groups pixels with high output values and takes the coordinates of the group center to detect *one* peak.

IV. Evaluation

The model was trained using the TensorFlow framework [1]. First, the model was applied to the validation dataset (Swiss territory between $46°$ and $47°$ lat. and $7°$ and $8°$ long.), so as to decide the threshold value for the formation of peak candidate groups ; afterwards such threshold was applied to the testing area (Swiss territory between $46°$ and $47°$ lat. and $9°$ and $10°$ long.). For the evaluation, we compared the list of peaks output by the CNN model with the ground truth, considering that a peak is correctly identified if its distance with respect to the closest ground truth peak, which is used as reference at most once, is less than a predefined threshold (200m). The problem under study comprises a very highly imbalanced nature, such that a cell of $1°$ of latitude and longitude containing 3,000 peaks would still contain around ≈ 10 millions negative samples. As suggested in [33] for this type of scenarios, Precision-Recall curve was the technique chosen for assessment over others such as ROC curve.

Figure 5 shows the precision-recall Pareto dominant curve of the CNN, varying the threshold of probability of being a peak for a point to be included in a candidate peak group.

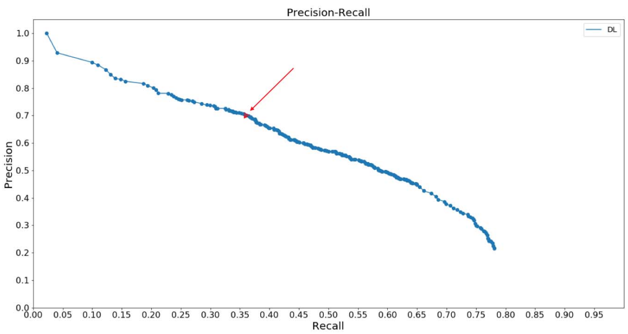

Fig. 5. Precision/recall curve of the CNN model on the validation set

Since the ultimate goal is to use these results as input for a crowd-sourcing tool to be validated, a balance between the amount of candidate peaks to be contributed (recall) and the crowd effort required (precision) must be achieved. For this reason, we chose the threshold value with precision above 70% with the highest recall. This is the threshold (99.934) of the point of the precision-recall curve shown in Figure 5, with precision = 70% and recall = 36%. We executed the corresponding model on the testing territory and, from this, we obtained 70% precision at 35% recall.

As mentioned, a discovered peak matches a ground truth peak if the distance is lower than 200m; the average distance of the True Positives peaks from the ground truth peaks in the test region is ≈ 52 meters. This distance can be further reduced by implementing smarter post-processing techniques to calculate the center of a group.

These results are preliminary and only relative to a very "difficult" region, where peaks are extremely dense and diverse; we expect to improve precision, recall and distance to the real peak by experimenting with alternative CNN models, training patch extraction strategies, and post-processing techniques. To conclude the evaluation, we provide some qualitative assessment of the obtained results. The following figures in this section were generated on top of [6]Cesium.

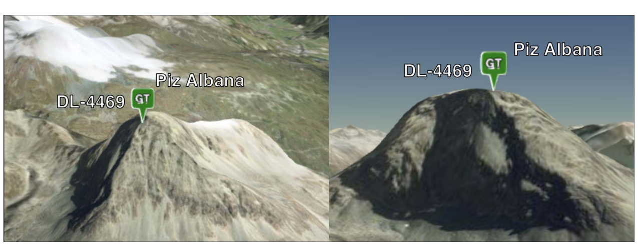

Fig. 6. Piz Albana, identified with 1m error

Figure 6 shows a group whose center was correctly identified as a mountain peak with ≈ 1 meter error. The green marker corresponds to the ground truth peak while the white marker corresponds to the estimated location of the summit.

Figure 7 shows that the DL method was able to identify a peak not listed in the ground truth, which we could identify inspecting a proprietary cartography. Since the mountain is not in the ground truth, the peak is classified as a False Positive, which lowers the computation of the precision. Using the coordinates from Wikipedia we calculated a distance error between the estimated and cartographic coordinates of 34m.

Fig. 7. Fil de Dragiva (Red): the DL identifies the point marked in purple as a peak; manual inspection in other data sources confirmed that it is a known peak, yet not listed in the ground truth

Figure 8 shows a peak in the ground truth that was missed by the DL model. Close to it, another point at a higher altitude in the same mountain (code named DL-648) is identified as a peak by the DL method, which is not listed in the ground truth. A visual inspection shows that it is not trivial to understand the difference between the two peaks and why one is listed as the mountain reference point and the other is not. The reason for DL-648 to be absent from the gold standard may be due to the incompleteness of the public data sets used to build the ground truth or to deeper reasons of history and tradition.

To cope with the uncertainty associated with the gold standard, we have developed a crowdsourcing framework, called MapMyMountains, which we plan to use to submit potentially mislabeled cases, such as peak DL-648, to a crowd of local mountain experts, so that they can validate if the peak is real or not based on 2D and 3D visualizations of the DEM, and, in the case the peak exists, provide metadata, such as the peak name. In this way, an iterative approach of ground truth refinement and model re-training can be used to improve the accuracy.

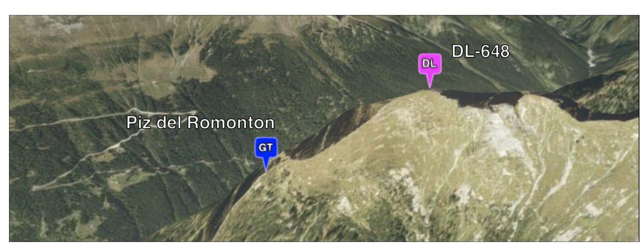

Fig. 8. False positive (purple) and False Negative (blue): Piz del Romonton

V. Conclusions and Future Work

In this paper we have discussed the use of Deep Learning for learning to find peaks in DEM data, an approach that to

[6]https://cesiumjs.org/

the best of our knowledge has not been employed in the past for this purpose. A preliminary evaluation in Switzerland, a region characterized by very dense peak distribution, shows promising results. Yet, the incompleteness of the gold standard and the fuzziness of the notion of mountain summit itself, call for a deeper study.

Our future work pursues a number of directions: 1) coping with label noise by applying data cleansing methods [14] and also by submitting the potentially mislabeled peaks to a crowd of local expert, for validation with the MapMyMountains application; 2) comparing the performance of DL with heuristic methods from the literature; 3) studying how the trained models generalize to mountain regions with different morphology; 4) refine our current model and experimenting other CNN architectures, such as U-Net [31], and other landform features; 5) exploring the use of geometric DL on graphs, applied to the topological network of landforms extracted from the DEM data [6]; 6) using ensemble learning to improve performance, by taking the best of image- and graph-based terrain representations and DL models.

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