Using Machine Learning to identify poverty in Lima Metropolitana with satellite imagery

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Introduction

- Peru: average economic annual growth of 6.1% [3].
- 2018: 20.5% of the population was in a situation of monetary poverty [3].
- Reduction of poverty as a priority in the National Plan towards the Bicentenary of Peru, in line with the number one goal of the millennium proposed by the PNUD [2].
- Poverty measurement in Peru - two main sources of data: the household surveys "Encuesta Nacional de Hogares" and national censuses.
- Limitations:
  - Its design only allows estimating income indicators per household with a level of regional or departmental representativeness [1].
  - High costs: the preparation and implementation of these require substantial human resources and budget for home visits, training processes and supervision of each stage.
  - Update frequency: household surveys are generally collected annually and the most recent estimates occur with a delay of more than two years.
- Satellite imagery: national coverage and periodic collection. PeruSat-1.

Dataset

The official document of the INEI "Stratified Planes of Metropolitan Lima at Blocks Level according to Household Per Capita Income 2016" presents a stratification of the census blocks of each district of the capital according to estimates of per household income. This report considers 5 strata: High, Medium-high, Medium, Medium-low, and Low [1]. Our dataset was constructed through multiple queries to the Google Static Maps API in order to extract images of several blocks of the document. Each of the 1280x1280 sized images spans a ground surface area of approximately 10 km2 and contains about 10 blocks of several districts of Lima. Our final dataset contains 1803 satellite images in total, 603 extracted from the API and 1200 new images generated with data augmentation.

Methodology

- Transfer learning approach, using a pre-trained CNN to extract the feature vectors of our images and a Support Vector Machine (SVM) classifier to perform the final classification.
- The methodology proposed is illustrated in the Figure 1.
- 4 classes (for each stratum [1]) : AB, C, D, and E, with class E being the one with the lowest level of income (i.e higher level of poverty).

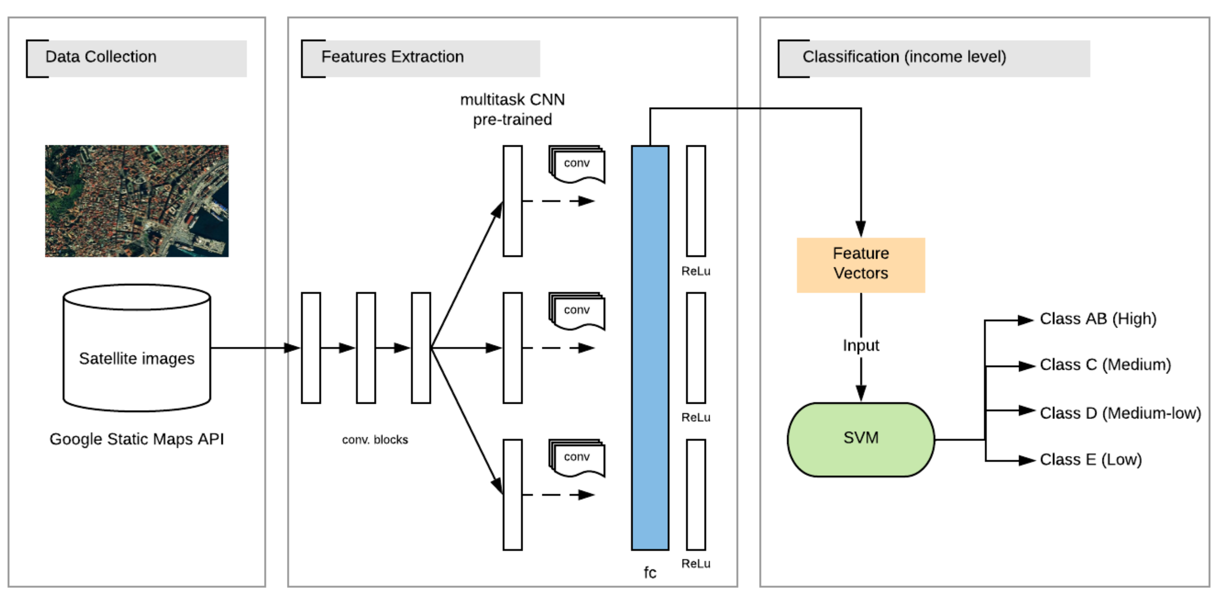

Figura 1: Proposed Methodology.

- Feature vectors (i.e descriptors) obtained through the elimination of the fully-connected layers of a CNN network pre-trained on a set of 47,120 satellite images from India to predict three simultaneous classification tasks: roof material, lighting source and drinking water source [4]. The satellite images, resized to 1094x1094 pixels were introduced as input data to said network and only the vectors (f.v) resulting from the convolutional blocks #9 and #10 of the architecture were extracted.
  - Three f.v of 1024 and 256 dimensions obtained, which concatenated sequentially resulted in unique f.v per image of 3072 and 3820 dimensions respectively.
  - Concatenation of the vectors of both convolutional blocks - unique f.v of 3840 dimensions generated.
- SVM classifier training: 80% images to train and 20% to validation. Standarization applied to all the feature vectors and GridSearch for hyperparameter optimization.

Results

In the Table 1 we can observe that using the characteristic vectors obtained from intermediate convolutional block 9 (768 dimensions) gives slightly better results (approximately 2% higher accuracy) than the characteristic vectors obtained from intermediate convolutional block 10 (3072 dimensions) in the final classification of the SVM. However, the best performance metrics obtained correspond to the use of a concatenation of the characteristic vectors of both intermediate layers (9 and 10). With this architecture, a general accuracy of 0.7479 and precision and recall measures for our target class (class E) of 0.92 and 0.88, respectively, are achieved. These results indicate that 92% of the satellite images classified by the model in class E actually belong to class E, while the recall measure indicates that only 88% of all the images of class E were correctly classified by the model as images corresponding to class E. It is worth mentioning that, for all cases, the precision and recall measures for classes C and D range between 0.61 and 0.78, which suggests that the models have difficulty in distinguishing the particular characteristics associated with each of these classes, which could due to the great visual similarity of satellite images of class C and class D.

Taula 1: Comparison of feature vectors extraction of different convolutional blocks.

	CNN (f.v 768) + SVM			**CNN (f.v 3072) + SVM**			**CNN (f.v 768+3072) + SVM**		
	Accuracy	Precision	Recall	Accuracy	Precision	Recall	Accuracy	Precision	Recall
Class AB	0.7146	0.66	0.71	0.7285	0.7	0.74	**0.7479**	0.73	0.71
Class C		0.62	0.75		0.61	0.71		0.63	0.75
Class D		0.78	0.61		0.76	0.63		0.78	0.68
Class E		0.9	0.84		0.92	0.88		**0.92**	**0.88**

Some of the details obtained by the various filters of the pre-trained CNN that were used to describe our images are illustrated in Figure 1. Here we can visualize the filters of the intermediate layers that are activated in the presence of elements such as highways, buildings, trees, and roofs.

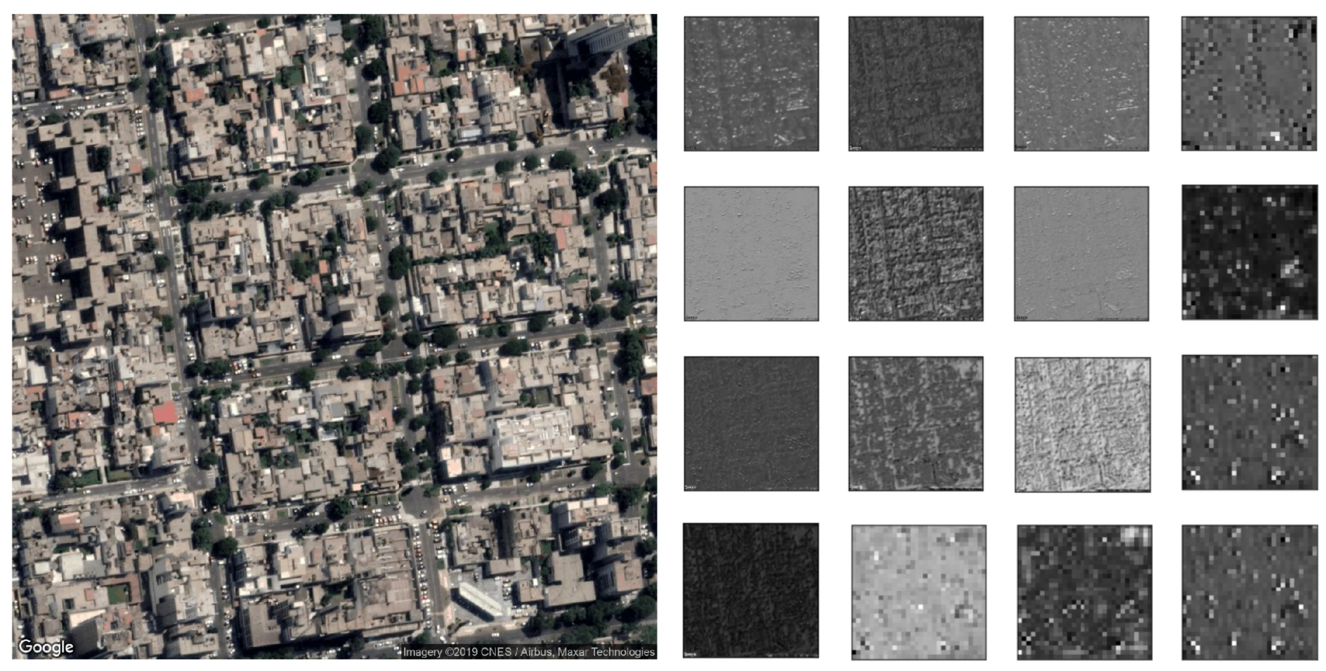

Figura 2: Filter activations for the pre-trained multi-task model.

Conclusions and Discussion

The combination of both techniques is useful for our main objective: to identify poverty. We successfully classified 88% of the satellite images belonging to class E. Although these results are encouraging, additional analysis suggests evaluating the possibility of testing this approach in other departments of Peru. It would be interesting to evaluate the performance of our model in heterogeneous geographical conditions in order to understand to what extent these results can be generalized for environments with different characteristics, such as regions of the Peruvian highlands and the Amazon.

References

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