Estimating Poverty in Bolivia through the Application of Deep Neural Networks

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***Abstract*—Poverty eradication is the first challenge of the Sustainable Development Goals (SDG) for Agenda 2030. By 2020, the World Bank preliminarily estimated the amount of poor people around the world between 703M and 729M. From that significant number, the Economic Commission for Latin America and the Caribbean (ECLAC) approximated that the total number of poor people in the region was 209M. In Bolivia, the ECLAC also projected the poverty rate to be around 34% of the total population in 2020, which would mean that about 3M people live in poverty. While there are many efforts to reduce these rates, a common obstacle that these initiatives face is how to properly locate the places that require more aid. Current approaches to gather such information rely on censuses and field-work, which is expensive and not performed frequently. Previous works explored the usage of Convolutional Neural Networks to assess if a given geographic area in Africa belongs to a poor region or not by using simple Satellite Imagery. Unfortunately, efforts focused on Latin America are scarce and, specifically, in Bolivia are non-existent to the best of our knowledge. In this work, we propose a model based on ResNet-50 .**

Delimit the department or locality based on public information and the availability of satellite imagery. Using a poverty measurement method already validated by the relevant institution. Once the images have been extracted, we use a deep learning backbone to classify the already labeled images. To finally compare our methodology applied for the first time in Bolivia with other state of the art projects.

Localized efforts to This project proposes a new approach to estimate poverty in Bolivia using machine learning and satellite imagery. La Paz was designated as the representative sample for image extraction and poverty categorization, using unsatisfied basic needs (UBN) surveys as a measure of poverty. The images were collected from google static maps using only RGB bands. The ResNet-50 architecture was used as a backbone for the categorization model. The best performing classification model has an accuracy of 86% for classifying population in poverty between 50.3- 74.3%. For poor population from 74.3 to 100%, it shows an accuracy of 80%. This project will serve as a tool to help demographic, social and statistical studies, by proposing a sustainable solution, since it only uses public resources. Proved scalability, as it grows according to the data and models used and is cost-effective compared to current methods for updating poverty data.

I. Introduction

The growing impact of Artificial Intelligence (AI) does not limit itself to pure technical contributions, but rather extends to Sustainable Development Goals (SDGs) [1]. In fact, Vinuesa et al. [2] showed that the field can positively contribute to the accomplishment of SDG's targets by identifying that at least 134 of the 169 targets may be enabled through it. From a general perspective, some targets as food security [3], gender equality [4] are already being discussed and addressed. Because of that, there are high expectations on the work that academia and industry are currently developing as well as engineering approaches for achieving justice and peace [5], [6].

Ending poverty in all its forms and everywhere in the world is the first goal of SDGs [7]. In the past, several tools have been developed to understand the distribution of poverty around countries [8], [9]. However, the required processes can be expensive to deploy as they require many people and resources. Thus, the assessment of poverty in poor regions or countries is relegated or postponed - Bolivia, unfortunately, is not an exception. Because of these difficulties, some works have focused on developing tools that are based on easy-to-access information to complement what data is already available as shown in [10], [11] [12].

Developing systems to measure poverty is one approach to solving it. There are many approaches to identify poverty conditions within a population [13], some are: Foster, Green and Thorbeke indicators, monetary poverty, living conditions, food safety and Unsatisfied Basic Needs. These involve surveys such as National Censuses, Demographic and Health Surveys (DHS), living standards measurement study (LSMS), among others, which are costly in terms of workforce and resources. In this context, any update required on the current state of poverty would imply investing time and money. Therefore, current explorations to assess poverty should include Cloud Computing methods to enable updating the information remotely and concurrently, so this information is accessible from different locations [14].

Remote sensing is a technique that aims at capturing, processing and analyzing digital images taken from different platforms [15]. Through these images, different works have analyzed patterns for diverse tasks as natural phenomena monitoring [16], aircraft detection [17], and even object localization [18]. Among remote sensing techniques, satellite imagery is usually remarked because it is globally available and represents a source of information with many advantages [12]. The information that can be extracted consists of a variety of data such as resolution, number of bands, multi-spectral and panchromatic characteristics, among others. However, the information is usually not structured or prepared for poverty prediction purposes, which makes necessary to work with different techniques for translating these data into useful features.

Following current trends on Computer Vision processing workflows, recent works based on Satellite Imagery introduced Deep Learning for effective feature extraction as in [19]. This combination allows to use invariant feature extraction and also, when predicting poverty, consider complementary variables as climate, land change, forestation, seasonality, and others []. The availability of these methods is advantageous given that, currently, there are several satellites that provide images with multiple resolutions for studying a diversity of patterns. Actually, Deep Learning methods represent a disruptive step in how cutting-edge machine learning tools can be used to solve main social issues.

In this work, we propose a model capable of estimating poverty in Bolivia by using a Deep Learning approach and satellite imagery. Our method is based on Transfer Learning and Deep Learning, also employs local statistical information to tag Satellite Imagery data. The rest of the paper is structured as follows: Section II reviews what related works can be found in the literature, Section III describes the methodology used, Section IV lists our results and discusses them to show their validity, Section V concludes the paper.

II. Related Works

Poverty estimation or prediction is an essential task for establishing appropriate public policies. Consequently, different works have been proposed aiming this goal using different approaches. In this section, we briefly review works that use Satellite Imagery.

In 2017, Engstrom et al. [20] explored how to use image features, like the number vehicles and roof material, as inputs of a simple linear model. Their results reassure that Satellite Imagery can be reliable used for poverty prediction, but at the same time they emphasize that more research is needed to assess the effectively of the approach when being used on different locations.

On the other hand, Andreano et al. [21], study poverty indices such as Poverty Headcount, Poverty Gap, and the Gini Index and their correlation with Night-Light Satellite Images, covering estimates from 22 years of data over the period 1992-2013 for Latin America and the Caribbean. This approach uses econometric literature with unbalanced regression models to estimate the correlation levels. Volumen de datos

In India, Pandey et al. [22] estimated economic and developmental parameters proposing a two step approach to predict poverty in a rural region from satellite imagery. The first step is focused on predict representative satellite image features such as: roofing material, lighting source and drinking water source. Subsequently, the model predicts income levels through a deep learning Multi-Task network. It is expected that these models may incur into misclassification given that different locations provide significant performance variations as authors also mention.

Furthermore, in [23], authors explored how to predict the household income of different locations or municipalities in different cities which size is considerable. Their results are motivating as they find that previously proposed models can provide good results in very different geographical places. A similar study was published by Ayush et al. []

https://arxiv.org/pdf/2002.01612.pdf (Object Detection)

Another research work with interesting results is the one by Tingzon et al [24], which propose apply a combination from grographic information from OpenStreetMap (OSM) and nighttime lights satellite imagery for estimating socioeconomic indicators. The interesting feature about this approach is the collaborative nature of its dataset. Gathering information from Demographic and Health Surveys (DHS), Nighttime Lights Data (from VIIRS DNB), Daytime Satellite Imagery (Google Static Maps API), Human Settlement Data (from Facebook) and OpenStreetMap Data (from Geofabrik). Their results conclude on: volunteered geographic information with satellite imagery are valuable tools for real-time poverty mapping.

Using a different approach there is the the research from Babenko et all [25], estimating poverty rates of urban and rural municipalities in Mexico with an end-to-end CNN. The poverty rates is measured by the poverty line well-being, consequently the estimation covers three buckets: below minimum well-being, between minimum well-being and above well-being. On the training process two architectures was used: GoogleNet and VGG, both have been used to predict poverty from satellite imagery in the past.

To understood if satellite imagery can be used to accurately measure welfare at the local level over space and time in Africa there is the work from Yeh et al [26]. They use a deep convolutional neural network to predict the particular village and year-specific wealth measure. The results show that their model is able to differentiate wealth levels within countries by being able to predict an avarage of 70% of the variation of country-year land bases wealth measures.

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A. Transfer Learning

Computer Science approaches to poverty measurement from satellite imagery have increased since [27], in which the authors propose a model for poverty prediction based on satellite imagery and Deep Learning. This research is a pioneer in using data concerning poverty collected by LSMS surveys, for labeling satellite imagery. The advantage of these surveys is provided by the geo-referenced coordinates of the surveyed households, in addition to using the international poverty line for measurement.

To solve the problem and perform a binary prediction of poverty in Africa, two transfer learning steps were used. In the first step pre-trained models were imported into ImageNet, which are recognized as good extractors of low-level features. In the second step the model was trained to predict nighttime light intensity levels from daytime satellite imagery. Electricity is a proxy for economic development, so the model is now trained to learn poverty-related features. Finally, the model is able to make a binary prediction of poverty.

B. Satellite Imagery

To solve the problem of expensive and scarce imagery to acquire, Perez et al [28] proposed a repository with Multi-spectral satellite imagery. The benefits of using this are publicly available, freely distributable also it's available for recent years. To supervise the training the Jean et al approach between night lights and predictions is used again.

To create the repository, images coming from satellite Landsat 7 on the African continent were used. Multi-spectral images have 9 spectral bands with a resolution from 60m/px to 15 m/px [29]. Several models were trained with the leave-one country out validation, to classify, nighttime light intensities: low, medium, and high brightness were used to label images. To deal with multi-band images, existing architectures like 18-ResNet and 34-ResNet had been adapted changing the first convolutional layer.

The squared correlation coefficient (r^2) was the assessment as a performance tool showing results since 0.63 was the lowest and 0.71 the highest. The performance model suffers in the countries that it has not seen before. This work concludes with the affirmation: predicting relative wealth in a single country is available, but may struggle across country borders.

Employing only images with RGB bands extracted from Google Static Maps we find the work of Head et al., [30] where LSMS surveys are used for dataset assembly and transfer learning with night light monitoring for feature learning. The model, based on the functionality was implemented in Tensorflow with the VGG16 backbone. The hyperparameters that were used included: CNN for feature extraction and learning, ridge regression, cross-validation, the image resolution was zoom 16 and the dataset was augmented using data augmentation techniques. The authors state that to fully investigate all possibilities, the parameters and hyperparameters of the machine learning algorithms should be systematically explored.

C. Big data

In order to predict poverty using satellite imagery and big data, there is the project: "Open data for algorithms: mapping poverty in Belize using open satellite derived features and machine learning". This project combines predictions from machine learning algorithms from satellite imagery with big data extracted from Labour Force Survey and national census. Two approaches are used, first: the contextual feature method, which analyzes spatial and spectral patterns within a neighborhood over a period of time. These features are helpful to understand the texture, orientation, complexity, and continuity of neighborhoods inside a cluster of pixels. The second approach analyzes time-series features by examining the change of each pixel over time.

The surveys were derived from the period April-September 2017, which fed the dataset to 3658 households, 75% were used for training and the remaining 25% for testing. The satellite images were statistically summarized at the geographic level, in order to capture spatial and temporal features. This information provides different r^2 correlation indices, as well as terrain indicators; building patterns, vegetation, and its relationship with poverty. These satellite data provide information about the house size, type of construction, land use intensity even indicators of successful or unsuccessful agricultural seasons.The paper concludes with the statement that data should be released to the public for research.

III. Methods

A. The Bolivian Context

Poverty is defined as the lack of resources that allow people to access the fundamental human needs [Definition source] As dehumanizing that poverty results, we need to address the disparities to generate: sustainable development and enhance living quality [why we need to think of finishing poverty]. There are several approaches to reduce poverty around the world, some of them are guided through the SGD UN objectives [include the roles of SGDs]. However, considering the vast amount of locations that are being considered as poor, a key concept to define where to put our resources is related poverty metrics [define metrics to approach poverty reduction policies]

The choice of poverty definition is very important, since different definitions imply the use of different poverty indicators [31]. Latin America recognize the definition: ”the situation of those households that are unable to gather, on a relatively stable manner, the necessary resources to satisfy the basic needs of their members” [32]. According to this definition, the methodology for measuring poverty indicators is carried out through surveys of Unsatisfied Basic Needs (UBN), which evaluate characteristics such as: economic activity, occupational category, housing, among others. This information about Bolivia is collected during the national census, which was last updated on 2012.

First, the geographic area was delimited for research based on publicly available and verifiable information, in addition of satellite imagery stock . In order to define and categorize poverty, the UBN surveys conducted at the municipal level by INE (National Institute of Statistics) were used. Two cities were considered: La Paz and Santa Cruz. Since both have the largest representative sample with 87 and 56 municipalities, respectively. At the end, it was concluded with the department of La Paz as the most appropriate for two reasons: since it gas more municipalities, there is more information to train the model. The second reason is the reproducibility of the model. La Paz geographically belongs to Altiplano (), together with the departments of Potosí and Oruro, where satellite images were available. Santa Cruz, on the other hand, belong to the tropical plains, as do the cities of Pando and Beni, whose representative sample of images is not available.

B. CNN framework

The paper is distributed in a sequential way, in the first stage we emphasize the poverty metrics to be used, because if we compare it with the literature, it differs quite a lot due to the context. The second stage of survey selection explains the source of information used to validate the model. In the categorization we observe how the data is distributed and therefore how it can be classified. The next stage is the assembly of the dataset, which is a particular feature in this task, since there are few images compared to the datasets used in the industry. The next step is the structure of the architecture, from pre-processing to the training of the last layers, for which a deep backbone was used. Finally, in the last stage it is possible to make the categorical prediction based on a set of images.

1) Dataset: The satellite images were downloaded and labeled according to the population poverty rate of their municipality. For this purpose, the UBN indices from the 87 municipalities of La Paz were analyzed by a histogram to study their frequency and distribution. The data were clustered on three categories to allow automatic classification: Class 1: [1%-38.3%], Class 2: [50.3%-74.3%] and Class 3: [74.3%-100%] see Figure 1.

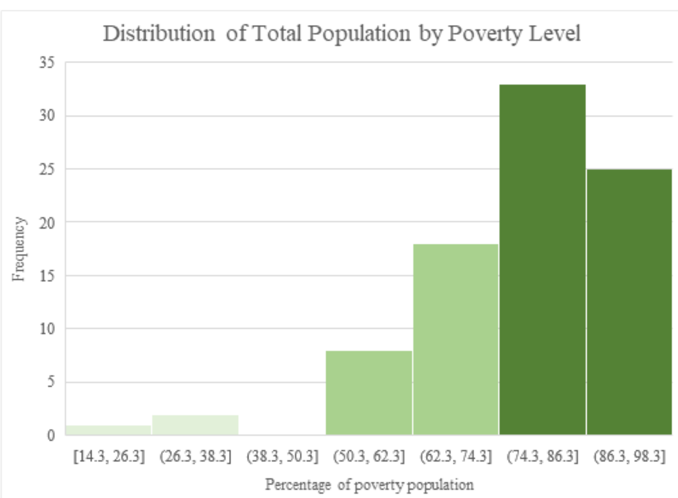

Fig. 1. Histogram of poverty distribution from La Paz

Two different datasets were used: A: 70%, 20% and 10% and B: 72%, 18% and 10% images which were distributed for training, validation and test, respectively. Both distributions are shown in detail on I 1 and II. To increase the size of the dataset, artificial images were generated with data augmentation techniques: rotation and translation on the horizontal and vertical axes.

	Category 1	Category 2	Category 3
Training	1354	1401	1400
Validation	387	400	400
Test	194	201	200
Total	1935	2002	2000

TABLE I
DATASET A

	Category 1	Category 2	Category 3
Training	1354	2628	1400
Validation	387	550	400
Test	194	360	200
Total	1935	3538	2000

TABLE II
DATASET B

2) Model: The first step was transfer learning, by importing pre-trained weights from ImageNet in order to recognize low-level features. The images were adjusted to 224x224 size and ImageDataGenerator was used to generate image blocks that were stored directly in the model and not in memory. The model built which was built on keras, was configured for three classes, also dropout was used turning off the 30% of the neurons to avoid overfitting. To train the model, the following configurations were performed on the hyperparameters: a Batchsize of 32, Softmax as activation function, Adadelta regularizer and 50 epochs for training.

IV. RESULTS AND DISCUSSION

Results for the best prediction results after several tests are found in Table III. It can be observed that for both models the accuracy has values higher than 60% on two out of three categories. Model A, which was trained with a balanced dataset, has an accuracy of 0.814 for category 1, 0.230 for category 2 being the least accurate and 0.972 for category 3.

A	Accuracy	Recall	f1-score	B	Accuracy	Recall	f1-score
1	0.814	0.757	0.784	1	0.529	0.861	0.656
2	0.230	0.948	0.370	2	0.856	0.655	0.742
3	0.972	0.577	0.724	3	0.795	0.836	0.815

TABLE III
COMPARISON BETWEEN MODELS PERFORMANCE

Studying the behavior of the A model, it can be observed that category 2 has false positives with a stronger tendency to category 3. This means that, model A does not find a determining factor to discriminate category 2 from the rest. According to the data distribution see (Figure **??**), the data trends to belong to category 3 than towards category 1. Which reflects that the model generalizes well for the extremes of the moderate poverty line and marginal poverty.

Model B has a different distribution as seen in the table II, an effort to improve the performance of category 2, it was used more data only on B dataset. The accuracy for this category is 0.856, a significant improvement over model A. While the accuracy drops for category 3 from 0.972 to 0.795, the model is still able to generalize features for marginal poverty.

Category 1 shows a decrease in precision between 0.814 of model A and 0.529 of model B. According to the results of the confusion matrix **??** category 1 reports false positives labeled as category 2. One way to increase the accuracy for this category is to increase the data size. However, since there are only 3 municipalities in La Paz labeled as category 1 and these were already used in the model, is not possible to increase the size.

The paper by Y.Ni et al., ”An investigation on Deep Learning Approaches to Combining Nighttime and Daytime Satellite Imagery for Poverty Prediction” [33] employs among others the ResNet-50 architecture for poverty prediction in Africa under the supervision of Night Lights. The results and performance metrics are given in Table V. Although it is not possible to compare their results with ours because both methodologies are different, it is possible to highlight the similarity of the accuracy results between ”high level” levels with category 1, ”medium level” with category 2 and ”low level” with category 3. It should be noted that the results of ”low level” as well as category 3 tend to be high. The results of ”medium level” and category 2 tend to have low results.

TABLE IV
PERFORMANCE OF THE SE-RESNET50 + FL MODEL BY [33]

Clase	Precisión	Recall	F1
high level	0.683	0.622	0.652
medium level	0.43	0.447	0.438
low level	0.947	0.946	0.964

A. Discussion

The standardization of the indicators of poverty used by the project was one of the biggest challenges. Since the work of [12] Xie et al. was the guide to follow, the lack of available data is critical. The state of the art has two surveys with poverty indicators at the household level, with geo-references for downloading images. In contrast, Bolivia only has the census surveys, and the minimum unit is a municipality, not a household. At this point the project takes the approach of standardizing poverty for an entire municipality and studying the distribution of data with a histogram. The result yielded a distribution of three categories, which supervise the training. In the state of the art, the intensity of night lights is used to supervise the training, and they also made a histogram that yielded three categories. This indicates coherence from our approach.

V. CONCLUSIONS

The national census collects a total of 86 variables which are subdivided into groups such as employment status, coverage of basic services and type of housing. All of these variables are directly related to unsatisfied basic needs. Since there are so many variables, studying them separately is a big challenge that must be analyzed with Big Data techniques. For this reason, the only UBN variables were analyzed using a histogram, a statistical metric to measure the frequency of an event. However, this approach used in Latin America is based on the coverage of needs; another valid metric is based on the international poverty line, which is based on consumption. Bolivia has this data at the macro level in each department.

Deep learning model allows to extract unstructured information from satellite images and abstract it. If the approach had been to manually label, the segmentation of these images, it would be a challenge to differentiate between satellite image features such as (ground, rivers, man-made constructions, crop fields, etc.). This particularly because many of these features need to be verified with field visits and not arbitrarily segmented.

The largest dataset used includes a total of 9947 images belonging to 83 of the 87 municipalities, counting the artificially generated images. Compared to other projects see IV, their dataset includes 98720 images, in addition to images of nighttime light intensity in geotiff format. Although there is no similar study done over Bolivia, even though there is a lack of data, both models present comparable results as others.

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