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Using Satellite Data to Guide Urban Poverty Reduction

Poverty reduction is increasingly an urban challenge, and a challenge that continues to be hampered by lack of data. One such example is the urban social safety net program, implemented by the Government of Mozambique, that is spatial in nature, but works without any data on the within city spatial distribution of poverty. The lack of detailed data on poverty is common in many developing as well as middle income countries.

This study applies Convolutional Neural Networks on high-resolution satellite images of cities in Mozambique, and combines their outputs with household level geo-referenced survey data. The results show that readily available data sources can generate detailed neighborhood-level poverty maps, providing key operational guidance for implementation of the urban social safety net. Importantly, the approach is highly automatic, applicable at scale, and cost-effective. It is thus a key step forward in the application of remote sensing image recognition for urban poverty reduction.

Previous studies relying on image recognition and machine learning methods for poverty estimation have focused mostly on rural or mixed urban-rural areas, and estimated poverty at village or municipal level, estimating average poverty levels for thousands of people[1-4]. Even single households' poverty status have been predicted using remote sensing data [5].

This study contributes to the nascent literature by estimating poverty scores (a PMT score) for locations smaller than 115 x 115m, which is an improvement on most previous. Importantly, unlikely the estimates at household level [5], that rely on manually measured structure footprints as a predictor, this study employs methods that run automatically and can be applied at large scale, utilizing data available in most countries. Further, the accuracy of these estimates is notably better than previous studies.

The study uses three separate Convolutional Neural Networks (CNN). It uses a CNN-detector to estimate the density of structures in urban areas, it uses a CNN classifier to estimate the quality and use of same structures, and finally it uses a CNN-regressor to estimate the poverty score directly, without defining any objects. In the preferred model, the CNN outcomes are combined with other spatial data as roads and distance to city center in a random forest prediction model, that provide estimates of average poverty score for small areas of the city. Figure 1 illustrates a simplified presentation of the data flow and models.

The model accuracy is presented in Table 1, while Figure 2 illustrates the outcome with an example from Maputo.

The outputs are used by the Government of Mozambique to guide their urban social safety program. Hence, the study shows that by applying novel methods to existing data, available in most countries, one can reduce the urban poverty data gap found in most countries.

Figure 1 here

Table 1 here

Figure 2 here