Poverty prediction by using deep learning on satellite images

The study split the datasets of satellite images of four (4) countries: Nigeria, Mali, Malawi, and Ethiopia obtained from Kaggle in 90% for training with 15% of it for validation and 10% for testing.

Literary review:

1. Piaggesi [2], in his work with his colleagues, investigated the economic livelihood prediction process in the urban ecosystem of two developed nations. They presented that the applied procedures for economic livelihood mapping in materials can also use low settings in this boundary. Categorically, they have precept that an algorithm pre-trained on the ImageNet dataset can elaborate on the target, an essential fraction of the variance with no adjust-tuning routine or proxies [2,5,13].
2. Pandey, Agarwal, and Krishnan [3] proposed a two-step method for estimating poverty in rural geo-regions of India from satellite imagery data. Firstly, they train a multi-task amply convolutional model to determine three developmental signs. The leading resource is the roof, source of nighttime lighting, and access to drinking water from satellite imagery. They observed that the multi-task amply convolutional model automatically understood symbolic features, like roads, settlements, agricultural lands, and water bodies. Secondly, they train a model to estimate the economic livelihood status (straightway indicator of poverty) using the first model's computed developmental parameter/value results [3,9].
3. Wu and Tan's article used Chongqing, China, to exemplify the application of the ResNet50 neural network model by analysing it in geo-regional economic research. Numerous experiments reveal the impact of satellite imagery and machine learning [16]. Their approach outperforms the direct use of sunset/nightlight imagery data to predict economic status. Moreover, the 'Squeeze-and-Excitation' roof/blocks are added into the Resnet50 model. The outcomes are also improved, which displays that the module can better increase the execution of the model and extract pattern features that better represent the economic level of the geo-region [4, 11, 16].
4. (Yeh et al., 2020) deep learning method also perhaps best regarded as a way to enlarge rather than replace traditional survey efforts, as local training data can frequently further increase model performance, and because other key living well-being outcomes often measured in surveys such as how wealth is shared between households, or among families within rural areas are harder to obtain in imagery. Likewise, they could also use their method to measure other key outcomes, including consumption-based poverty metrics or other essential livelihoods directional such as health results [4, 11].
5. (Kondmann, Zhu., 2020) Results outline that pioneering approaches that map poverty from satellite images with deep learning may struggle to capture trends in economic development over time [5]. Thoroughly validating these results in other countries and with other imagery is necessary to communicate the robustness of this weakness [5, 12].
6. (Head et al., 2017) The research presents a preliminary evaluation of the globalisation ability of satellite-based approaches for predicting human development after replicating past studies that reestablished the potential for such techniques to estimate asset worth based in Rwanda [6]. They explained that the same method could not be trivially interpreted into evaluating other “softer” development outcomes (like health outcomes and source to clean drinking water) with the same correctness in other countries (precisely like Haiti and Nepal) [6, 13].

7. Angelini and Colleagues' work advances their previous study into picture-based models of economic livelihood situations using satellite imagery. Their study outcomes for three African countries are similar to their earlier studies of three different African countries using high-resolution public imagery [17].
8. The work of Engstrom and his research partners [18] shows results that spatial and spectral patterns did adequately well on their own at elaborating economic livelihood, with adjusted R2 number starting from decimal 0.46 to 0.54. After all, they also discover the spatial autocorrelation in the framed procedural residuals, which shows that significant explanatory variables are reducing or absent from the models. But, it is not surprising, especially when considering the complicated nature of urban economic livelihood. It is more significant than an essential precursor and rise of the spatial set-up of onthe-ground objects [18, 6, 13].
9. Irvine, Wood, and McBee [19], in their analysis of some selected sub-Saharan African geo-regions, image-derived patterns provide essential data for estimating survey answers across a range of questions. The achievement is commonly most substantial with questions on infrastructure, like accessibility to electricity, clean water, shelter, healthcare service and sewage disposal. Social behaviours can also involve questions, but they act only slightly greater than chance. Compared to their results from the earlier study conducted in Afghanistan, the achievement in this work is less compelling [19].
10. In the paper [20], Das, Chhabra, and Dubey viewed that 'from applying the first standard techniques of gathering data on paper, to using technology that was not yet really explored in this specific domain, the goal was usually alike: Reduction of Global Poverty. They outline that this can be performed only with a correct poverty map of the earth. Figuring observations from numerous researches, it is clear that satellite imagery information mixed with different approaches studied for this paper or otherwise looks like the best means by which the universe needs to move forward and solve this significant global problem. The accumulated solutions can be helpful in policy-making by policymakers to develop frameworks that can work actively at all classes or levels [20, 8].
11. From their World Bank publication, Engstrom, Hersh, and Newhouse [26] question how well economic livelihood status derived from satellite imagery predicts poverty and which position is most significant? They examine these questions using a research segment of 1,291 villages in Sri Lanka, connecting parameters of economic well-being level with features or patterns obtained from high-resolution satellite imagery.
12. Okaidat and study peers [27] regard that 'number one objective of sustainable development goal (SDG) is to overshadow poverty.' The scholars primarily outline procedures to recognize the spatial distribution of economic livelihood. The data that Okaidat and peers [27] used in their project contains three datasets that involve satellite images for three nations: Malawi, Ethiopia, and Nigeria. They used 30% of every dataset for testing and 70% for training. They also use 20% of the training set for validation. They applied Convolutional Neural Networks (CNN) classifier with particular architecture to classify or segment the satellite images of Malawi, Ethiopia, and Nigeria into three groups related to three countries with various poverty levels. Class 0 is correlatedly assigned to Ethiopia, with the lowest economic livelihood status; class 1 was connectedly set to Malawi with the intermediate financial position.

And class 2 was correlatedly assigned to Nigeria with the highest economic livelihood status [27].