Poverty Prediction **Using** Satellite Imagery **And** Machine Learning

Rekha S. Thorat, Dr. Praveen C. Shetiye, Dr. Avinash K. Gulve

Abstract: Poverty is a major problem in developing countries as it becomes an obstacle to development. Identifying poor areas is a big task for the government to make policy. Earlier household survey method takes more time, effort and cost. To overcome this limitation, the method of predicting poverty using satellite images is covered in the paper. Composite data of nighttime satellite images of Rwanda country of Africa is taken from DMSP-OLS's satellite series under EOG of NOAA is trained with a Regression model. 5 night light intensity features used to train the Regression model with a label of DHS data of Rwanda which includes latitude, longitude and respective wealth index. The result shows there is a good correlation with night light intensity and wealth index with R^2 of 0.752. In the second experiment daytime satellite images taken from Google static maps, extracted 4096 CNN features and trained with the CNN model using transfer learning. Which also gives a good result with 82% testing accuracy. Thus both the experiment reveals that satellite data and machine learning can be a useful technique for estimating poverty.

Index Terms: DHS, CNN, Imagenet, satellite imagery, household survey, transfer learning, poverty.

I. INTRODUCTION

Poverty is the main obstacle of development in developing countries; government organization designs various policies to recover from it. To apply those policies it is necessary to identify poor areas. And to identify poor areas various methodologies are used like household survey, GDP (gross domestic product) [1] etc. But those traditional methodologies have many limitations in case of time, effort, and expensive. The household survey requires more time, more efforts and money. To do the household survey it needs to reach each doorstep in the country, collect all the data of each house, organize it, analyze it and then make policies accordingly, this lengthy process slows down the rate of development in the country. Earlier GDP statistical analysis was used to track socioeconomic activities. But it had many limitations as it does not differentiate costs from benefit and not distinguishes sustainable practice from unsustainable ones [1]. Also the GDP gives less accuracy. Data availability is consequently scarce and it is not updated regularly. To overcome these limitations poverty prediction using satellite images with machine learning can be applied. Satellite images are freely available for research purpose and are up to date. And machine learning methods give optimum accuracy and require less time for processing. Nighttime data already used to estimate the population, coal consumption, electricity consumption in a country. Also, the daytime data is used for object detection in images like buildings, structure of building, roofs, roads, rivers, plants and many more. It also has the potential to predict poverty in less time [2].

- *Dr. Ryan Engstrom (a member of the Department of Geography) worked on the case study area of Srilanka and calculated 165 spectral and spatial features to estimate poverty. The features calculated include linear binary pattern moments (LBPM), linear support regions (LSR), PanTex, Speeded Up Robust Features (SURF), Histogram of Oriented Gradients (HoG), Fourier Transform (FT), Gabor, the mean of each of the red, blue, green and near-infrared spectral bands, as well as the Normalized Difference Vegetation Index (NDVI) [5]. And it is observed that these features were able to identify the change in poverty about 54% using the linear regression method.*
- *Shailesh M. Pandey in 2018 uses multi-task deep learning transfer model to detect poverty from satellite images using 3 features-material of the roof, source of electricity and drinking water. And fully connected multi-task convolution model trained using these features [4].*
- *Joshua Blumenstock uses the different approach, he uses mobile phone metadata with census data to estimate poverty. The survey was done with 865 mobile phone subscriber and questionnaire.*

So that policies can be applied in time to the areas it needed, which will increase the rate of development in the country. In this paper combining satellite images of nighttime and daytime with machine learning methods, Regression and CNN are used to poverty area detection. DHS(demographic health survey) data used to train the machine learning model with remote sensing data. And then use that model to predict poverty using only satellite images. Now a day's machine learning technology is growing rapidly with strong algorithms and less time complexities, therefore, it can be used to solve these socioeconomic problems. Also the electronics technology is developing rapidly so that more accurate remote sensing data is easily available. Thus combining Machine learning and remote sensing data to predict poverty will give more accuracy than now in the future.

II. RELATED WORK

Earlier researchers have done work on poverty prediction using various methodologies. In 2007 Christopher D. Elvidge who is a member of Earth Observation Group shows that satellite data has a potential to detect poverty. For this, they represented observed radiances from nighttime lights versus population count for three cities. Their observation shows that there is dim light or no light in the poor area and bright light in a developed area which opens the door for further researches [3]. In 2009 students of IIT demonstrated that there is a sharp increase in the amount of impervious land, decrease in open spaces, shrinking of fertile agricultural lands, reductions in vegetation cover, decrease in water bodies and its effect on urban poverty. Pre-trained model is used to extract feature from daytime satellite image in their experiment of resolution 1920×1920 at a zoom level of 16 and CNN is used to train the model [4]. After that Neal Jean used 3 methods OLS, Lasso and Ridge with R^2-0.327, 0.339, 0.331 respectively. He uses census data to train these regression models [2].

III. DATASET

In the project a model is developed to predict poverty through satellite images only, it is necessary to train it with household survey data also. Therefore both satellite images and household survey data is taken.

A. Satellite data

Both night time and daytime satellite imagery are used in the project. Nighttime satellite images are taken from the Defence Meteorological Satellite Program (DMSP) which operates a series of satellites which carry very sensitive light sensors are known as the Operational Linescan System (OLS) that can detect light emission from the earth surface at night. DMSP-OLS can capture the faint light of visible near-infrared emission present at night on Earth. Most of the data received by NOAA-NGDC is in the smoothed spatial resolution mode [7]. Composites are made as an average of the highest quality nighttime lights imagery over the desired time period – usually monthly or annually. The products are 30 arc-second grids, spanning -180 to 180 degrees longitude and -65 to 75 degrees latitude and are cloud-free. A stable light composite nighttime satellite image is used in a project of 43201*16801 dimensions and 1 dpi.

B. Day-time Satellite images

Daytime satellite images are downloaded from Google Static maps at zoom level 16 with a pixel resolution of 2.5m. Each image used is of 400 X 400 and 96dpi which covers 1 kilometer square area. In the project, images are converted to 224 X 224 dimensions [8]. Total 35000 images are downloaded and used for the project by providing longitude and latitude in URL of request query. To use images Google map API key is required which has a daily limit of usage.

C. DHS data

Demographic health survey (DHS) is a standard survey at most conducted in every country. Data collected on various indicators like population, health, nutrition and wealth which are used by the respective government of the country to make policy and to monitor different aspects. Information is collected for various topics like health, education, domestic violence, family planning, women empowerment, gender/domestic violence, addiction and wealth [9].

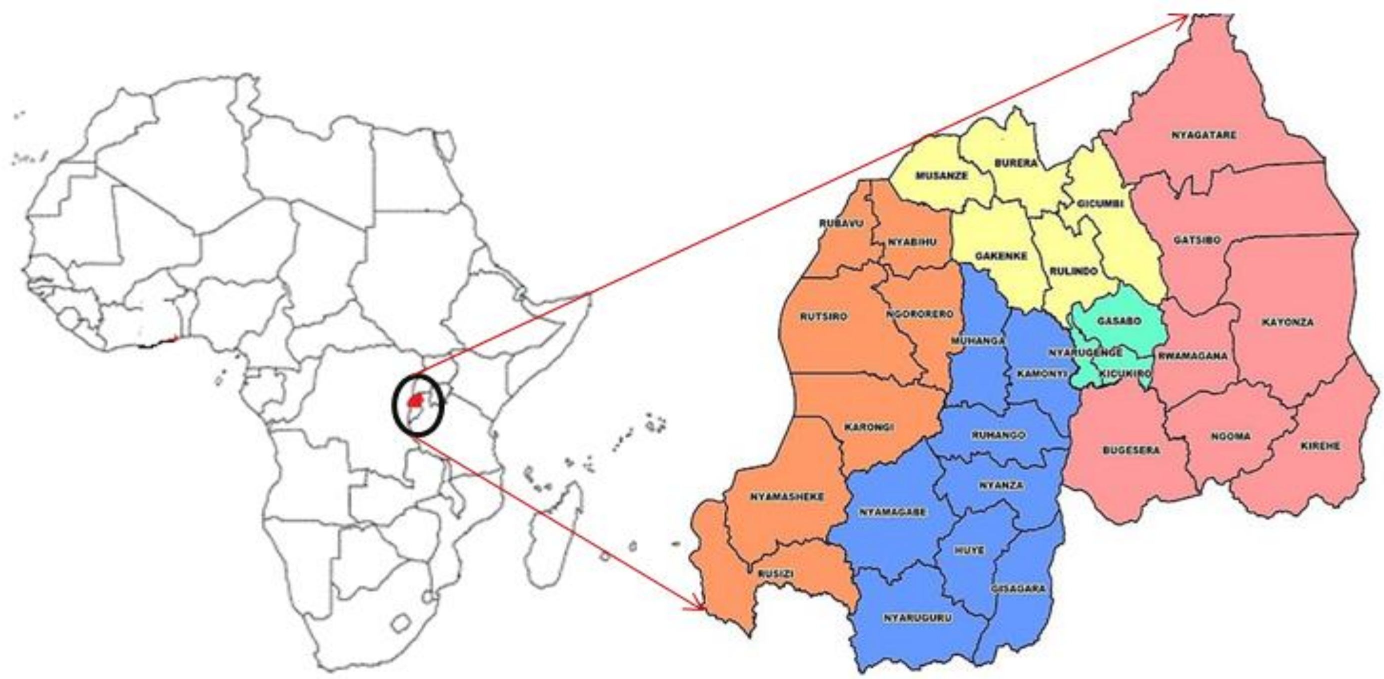

Figure 1: *Rwanda country in the map of Africa*

There are two types of DHS survey type:

1. Standard DHS Survey

   It contains a large sample size between 5000 to 30000 households having lots of questionaries' to collect brief data of each house. And this type of a survey is generally conducted about every 5 years to compare the different aspects, which is helpful for developing countries to make policies accordingly.

2. Interim DHS Surveys

   It is conducted to collect information about specific topics and it requires less time for the survey because contains fewer questionnaires.

In the project, standard DHS survey data is used of the year 2010.

D. Case Study Area

Rwanda is one of the smallest country in central and east Africa shown in Figure 1., which covers 24,668 km^2 land area and with a latitude of 1.9403°(1°57'S) and longitude of 29.8739°(30°7'E). The country is organized in four provinces in addition to the Kigali city, 30 districts, 416 Sectors,2148 Cells, and 14 837 Villages. Major cities of Rwanda which is studied in the project are shown below in the table:

TABLE I

Coordinates of Rwanda cities

City	Coordinates
Kigali	-1.94995, 30.0588493
Butare	-2.5966699, 29.7394409

Gitarama	-2.07444, 29.75667
Musanze	-1.49984, 29.6349697
Giseny	-1.70278, 29.2563896
Byumba	-1.5763, 30.0674992
Cyangugu	-2.4846001, 28.9074993
Kibuye	-2.0602801, 29.3477802
Rwamagana	-1.9487, 30.4347
Kibungo	-2.1596999, 30.5426998
Nzega	-2.4790001, 29.5564003
Eglise Catholique, Centrale GIKO	-1.93653, 29.8061008
Gikongoro	-2.4639699, 29.5738907
Nyanza	-2.3518701, 29.7508907

IV. METHODS

A. Construction of light to wealth index relationship

• Rwanda country is divided into 492 clusters along with latitude and longitude which is then joined with DHS data. DHS data contains latitude, longitude, cluster number, wealth index, and many more parameters. Then both the cluster location and DHS data joined together on latitude and longitude. In this step, each cluster is assigned with some value of wealth index.

• In next step, night time satellite image is processed and statistics parameter of the light index are calculated cluster's latitude and longitude wise. All these statistics parameters like minimum value from all intensity value in a satellite image, standard deviation value, mean value, median value, and mode value is stored cluster wise in a file.

• In the final step above two relational tables is joined on cluster's value which will give cluster number, wealth index and statistics parameter of light intensity.

• For daytime satellite images also same steps are done.

B. Rgression

• Multiple features from image mean, median, mode, standard deviation, and max are used to predict the wealth index at that particular cluster, therefore ridge regression model is trained to perfectly fit and to overcome the limitation of over fitting the training set.

• Kfold is used to split the training and testing data into splits of 10.

• Label wealth index is used with five features.

C. Imagenet

Like nighttime satellite image's feature, features of daytime satellite image are also calculated using the pre-trained model called Imagenet. By with total 4096 features are retrieved for each cluster [10].

D. CNN

By using daytime features extracted through Imagenet to predict wealth gives less accuracy and R2(regression coefficient) is below 0.5. To overcome these daytime features are trained again using transfer learning.

• There are 5 nightlight features (min_, max_, std_, median_, mean_) calculated from night time satellite image of Rwanda with its latitude and longitude.

• And 4096 daytime features (CNN features) calculated from daytime images with latitude and longitude.

• Then daytime images divided into 3 class of light intensity-low, medium and high using the night light features of corresponding latitude and longitude.

• After training the CNN model night time intensity is predicted first using daytime features of images in transfer learning.

• And then the wealth index is predicted through night time features.

	id	max_	min_	mean_	median_	std_	wealth
0	1.0	6.0	0.0	0.06	0.0	0.596992	-0.531405
1	2.0	0.0	0.0	0.00	0.0	0.000000	-0.409830
2	3.0	0.0	0.0	0.00	0.0	0.000000	-0.478115
3	4.0	0.0	0.0	0.00	0.0	0.000000	-0.435960
4	5.0	0.0	0.0	0.00	0.0	0.000000	-0.449480
5	6.0	26.0	0.0	6.08	6.0	6.837660	-0.112650
6	7.0	0.0	0.0	0.00	0.0	0.000000	-0.399620
7	8.0	0.0	0.0	0.00	0.0	0.000000	-0.195580
8	9.0	62.0	7.0	36.67	36.0	18.668720	2.395540
9	10.0	0.0	0.0	0.00	0.0	0.000000	0.056460
10	11.0	0.0	0.0	0.00	0.0	0.000000	-0.233975
11	12.0	0.0	0.0	0.00	0.0	0.000000	-0.458450
12	13.0	0.0	0.0	0.00	0.0	0.000000	-0.643445
13	14.0	0.0	0.0	0.00	0.0	0.000000	-0.501530
14	15.0	0.0	0.0	0.00	0.0	0.000000	-0.490690
15	16.0	0.0	0.0	0.00	0.0	0.000000	-0.548980
16	17.0	7.0	0.0	0.20	0.0	1.140175	-0.412520
17	18.0	0.0	0.0	0.00	0.0	0.000000	-0.419030
18	19.0	0.0	0.0	0.00	0.0	0.000000	-0.380060
19	20.0	8.0	0.0	0.80	0.0	2.177154	-0.460620
20	21.0	0.0	0.0	0.00	0.0	0.000000	-0.266005

Figure 2: *Nightlight intensity features used to train model*

V. RESULT

In the proposed system 4 machine learning models are used.

A. Ridge regression for night time satellite imagery

Using this method regression coefficient is calculated to find the relationship between the light index of nighttime satellite image and wealth index. And the result shows that there is better correlation between those two variables.

In Figure. 3 mean value of the light index is correlated with average wealth index from DHS data and in Figure. 4 max value standard deviation value of the light index is correlated. When all the statistical features of the light index(mean, median, standard deviation, min, max) is used to train the ridge regression model it gives better result with R2 0.752.

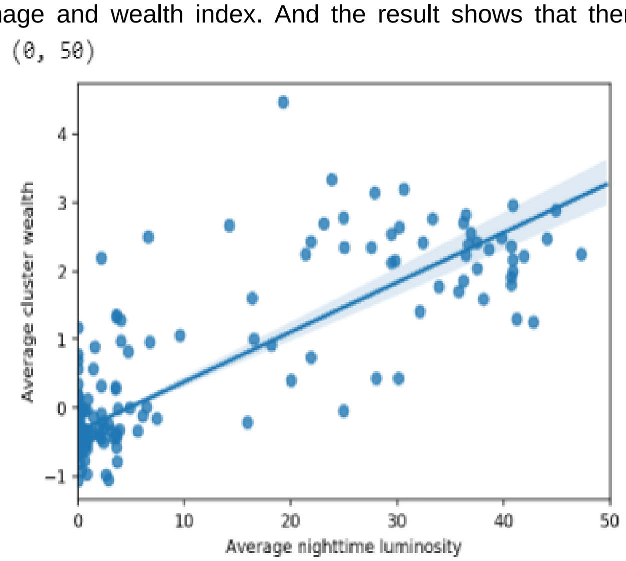

Figure 3: *Correlation between a mean of night light light intensity and wealth index*

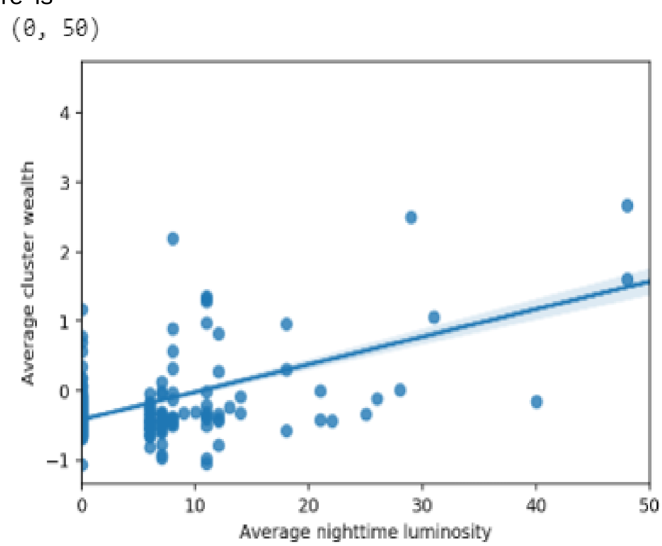

Figure 4: *Correlation between a standard deviation of night intensity and wealth inde*

B. Ridge regression for daytime satellite images

To extract features from daytime satellite images VGG16 model is used and total 4096 features are extracted and passed to train Ridge regression model. It gives R2 of 0.496.

C. Transfer learning Approach

In this approach daytime satellite feature are again trained by

VGG16 with nighttime features which give more accuracy.

TABLE II

Performance analysis of machine learning models

Model	No of features	R^2/ accuracy (%)
Ridge Regression model for nighttime satellite imagery	5	0.752
Ridge Regression model for daytime satellite imagery	5	0.331
VGG16 and Ridge Regression for daytime satellite imagery	100	0.496
VGG16 and CNN for both daytime and nighttime satellite imagery	4096	75

VI. CONCLUSION

Results in this paper show that the proposed method of poverty prediction using satellite data is an effective alternative to household survey and covers the limitation of time, cost and effort. Traditionally, statistical analysis on DHS data is used as a measure to predict poverty which lacks reliable and updated data. Remote sensing data is updated regularly. Nighttime satellite images are easily available from EOG of NOAA/NGDC's DMSP-OLS satellite series and daytime satellite data available from Google static maps. Also, the advancement in machine learning algorithms for image processing makes a scope for this research. But there are some limitations of this proposed system: 1) The model trained can be used countrywide only, as there can a different relationship between light index and wealth index for different country. 2) Satellite images used in the proposed system contain some noise. Therefore there is a need to design more general model for all countries and to use advanced image processing to resolve noise.

VII. REFERENCES

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