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Introduction

- The elimination of poverty worldwide is the first of 17 UN Sustainable Development Goals for the year 2030.
- Around 1.85 billion people, or 36% of the **world's** population, lived in extreme poverty. Nearly half the population in developing countries lived on less than $1.25 a day.Nov 21, 2018 (www.worldvision.org)

Introduction

- The lack of reliable data in developing countries is a major obstacle to sustainable development, food security, and disaster relief.
- Poverty data, for example, is typically scarce, sparse in coverage, and labour-intensive to obtain.
- Remote sensing data such as high-resolution satellite imagery, on the other hand, is becoming increasingly available and inexpensive.
- Unfortunately, such data is highly unstructured and currently no techniques exist to automatically extract useful insights to inform policy decisions and help direct humanitarian efforts.
- We here demonstrate a novel machine learning approach to extract large-scale socioeconomic indicators from high resolution satellite imagery.

Problem statement

- Here, the problem which we are trying to solve is predicting poverty levels at different geographic location on the earth because poverty data available right now is typically scarce, sparse in coverage, and labor-intensive to obtain.

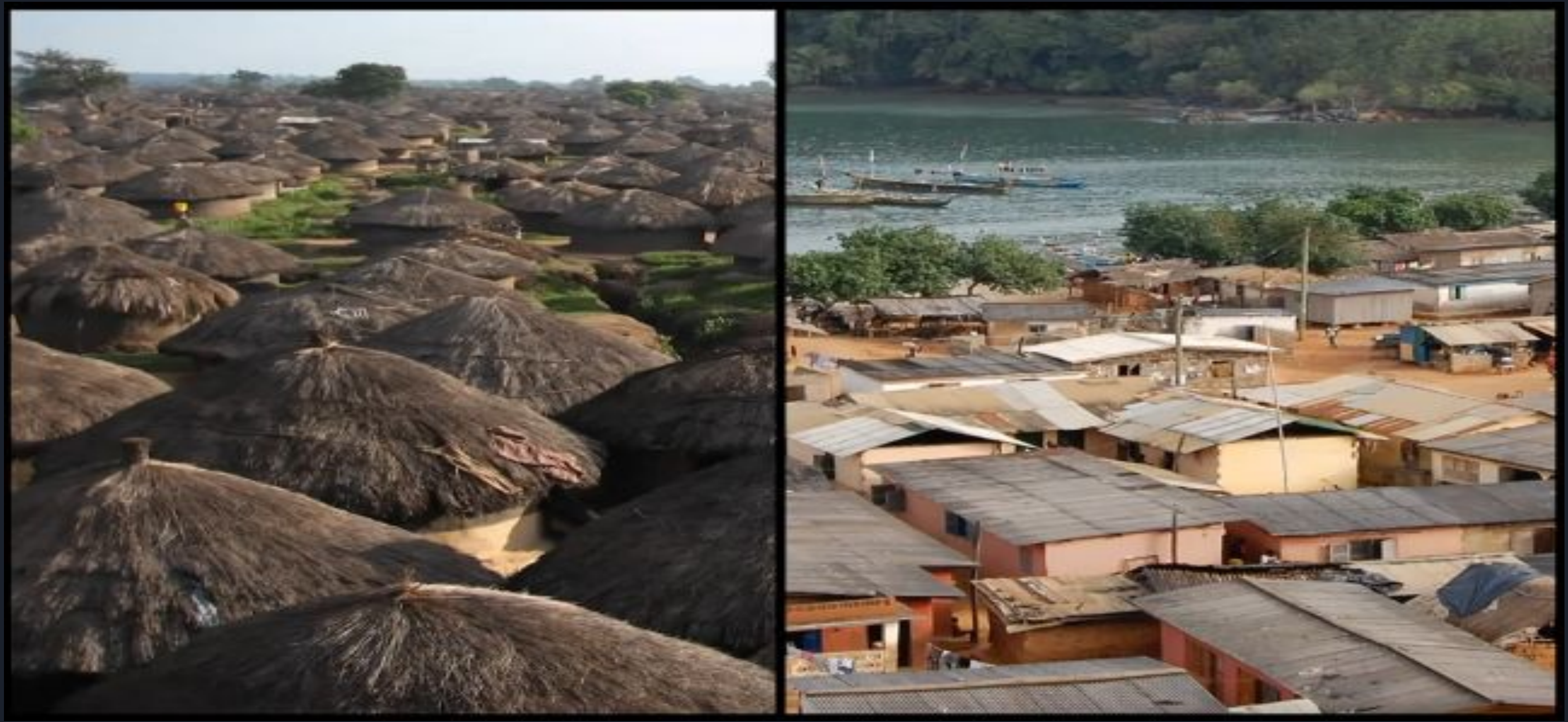
- Also the traditional methods used for obtaining this data like household surveys and census are small-scale and expensive.

- Thus, we are trying to solve this problem by combining powerful machine learning algorithms and high resolution satellite imagery, which are perhaps the only cost-effective technology able to provide data at a global scale.

- Inshort, we will be taking high resolution satellite imagery as input and will provide poverty mapping on a map of a particular country or on a particular geographic location in the form of heat maps.

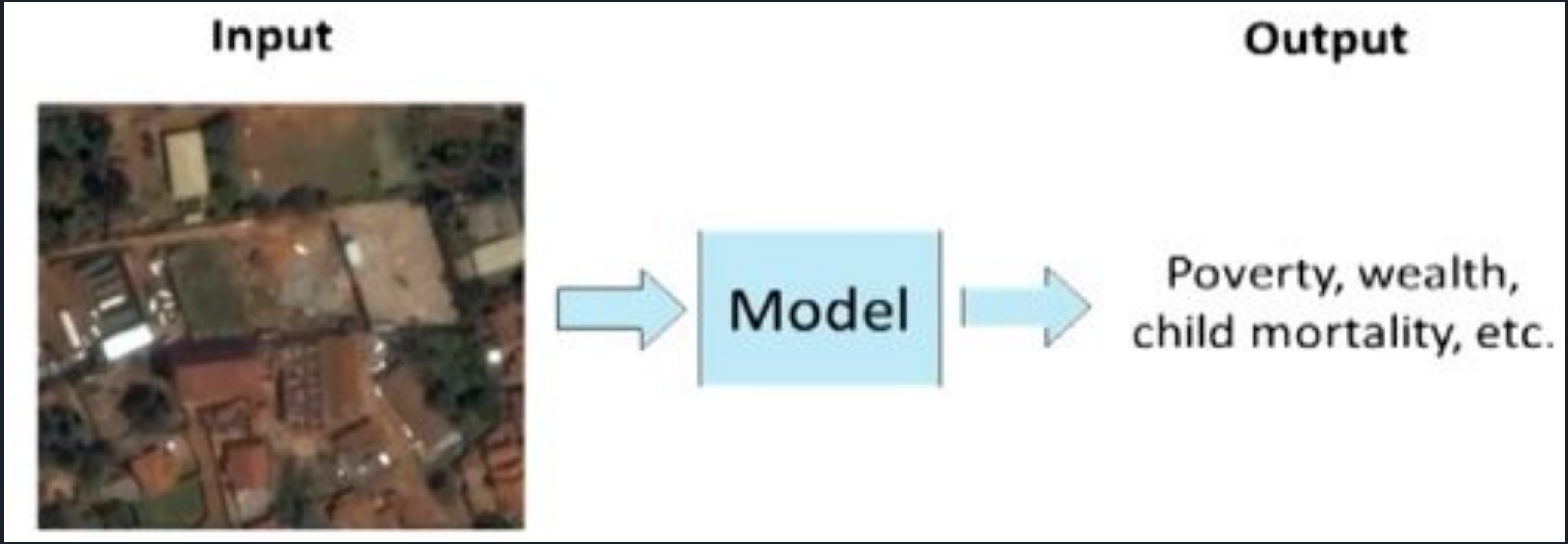
Traditional Method

- One of the traditional ways used, is to do survey at home to home basis to collect data.
- About the traditional way we all know that it is very time consuming. It can cost a lot of human efforts and money.
- This surveys' covers around 0.01% households.
- There are great chances of human errors in these type of surveys' and hence they are not much accurate and reliable.
- Also in these type of household surveys' for poverty estimation many poorest population become invisible.
- These type of surveys' have also proved to be dangerous because in some african remote countries, the humans conducting surveys' have claimed about danger to their lives.
- Period of conducting these type of surveys' is 5 to 10 years.



A normal picture in the Africa

High-resolution daytime satellite imagery



- ➔ Above Diagram shows our main goal, but this is not as simple as it looks because there is very little labelled training data.
- ➔ It is also non trivial for humans to manually setting up the labels.
- ➔ So this problem is stopping us from using the standard supervised learning approach.

Techniques Used in This Project

- ➔ The main challenge is that training data is very scarce, making it difficult to apply modern techniques such as Convolutional Neural Networks (CNN).
- ➔ We therefore propose a transfer learning approach where nighttime light intensities are used as a data-rich proxy.
- ➔ We train a fully convolutional CNN model to predict nighttime lights from daytime imagery, simultaneously learning features that are useful for poverty prediction.
- ➔ The model learns filters identifying different terrains and man-made structures, including roads, buildings, and farmlands, without any supervision beyond nighttime lights.
- ➔ We demonstrate that these learned features are highly informative for poverty mapping, even approaching the predictive performance of survey data collected in the field.

Convolutional Neural Networks (CNN)

- A **convolutional neural network** (**CNN**, or **ConvNet**) is a class of deep neural networks, most commonly applied to analyzing visual imagery. It consist of following steps in its operations:
  - Convolution Operation
  - ReLU Layer
  - Pooling
  - Flattening
  - Full Connection
- Modern approaches such as Convolutional Neural Networks (CNN) can, in principle, be directly applied to extract socioeconomic factors, but the primary challenge is a lack of training data.
- While such data is readily available in the United States and other developed nations, it is extremely scarce in Africa where these techniques would be most useful.

Transfer Learning (TL)

- Transfer learning (TL) is a research problem in machine learning (ML) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem.
- For example, knowledge gained while learning to recognize cars could apply when trying to recognize trucks.
- The low-level and high-level features learned by a CNN on a source domain can often be transferred to augment learning in a different but related target domain.
- For target problems with limited amounts of data, learning new high-level features is difficult.
- However, if the source and target domain are sufficiently similar, the feature representation learned by the CNN on the source task can also be used for the target problem.
- In our approach to poverty mapping using satellite imagery, we construct a linear chain transfer learning graph which is demonstrated in the following slides.

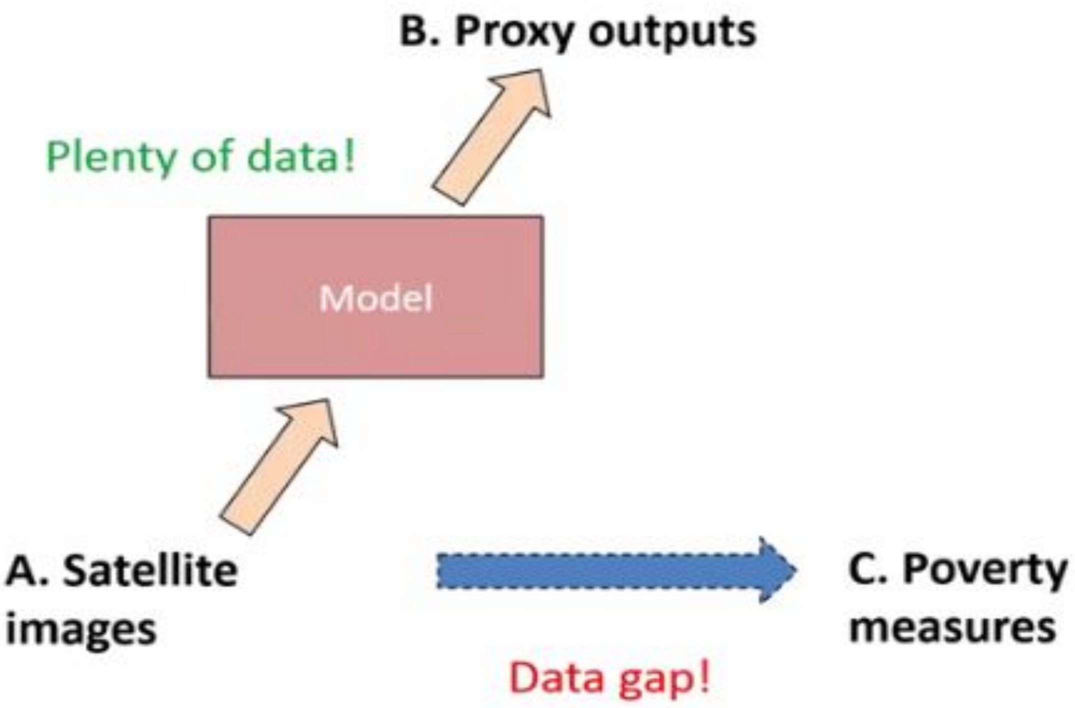
Transfer learning bridges the data gap

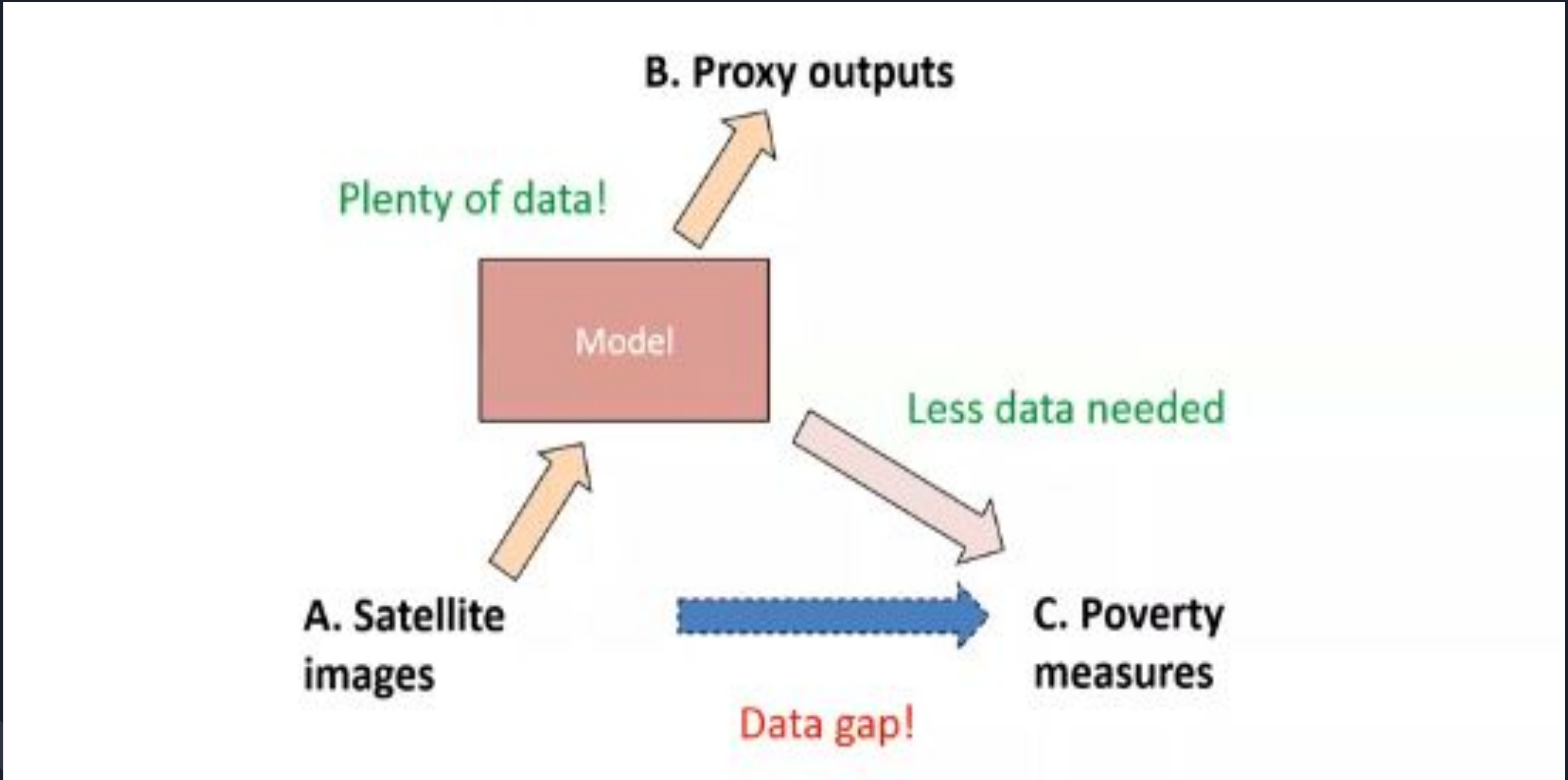
A. Satellite images

C. Poverty measures

Data gap!

Transfer learning bridges the data gap





Transfer learning bridges the data gap

- ➔ Nightlight Data works as proxy data.
- ➔ It is good indicator for socio economic development.
- ➔ In the image we can see that south korea is brighten up at night whereas north korea is dark.

Solution Approach

Aim : To map poverty using satellite imagery

Steps : We distributed our problem statement into a series of sub-problems:

P1 : Object recognition task on images using pretrained model of ImageNet
P2 : Prediction of nighttime light intensity from daytime satellite imagery
P3 : Prediction of poverty from light intensity and daytime features which we got from P1 and P2

Recognizing the differences between ImageNet data and satellite imagery, we use the intermediate problem P2 to learn about the bird's-eye viewpoint of satellite imagery and extract features relevant to socioeconomic development.

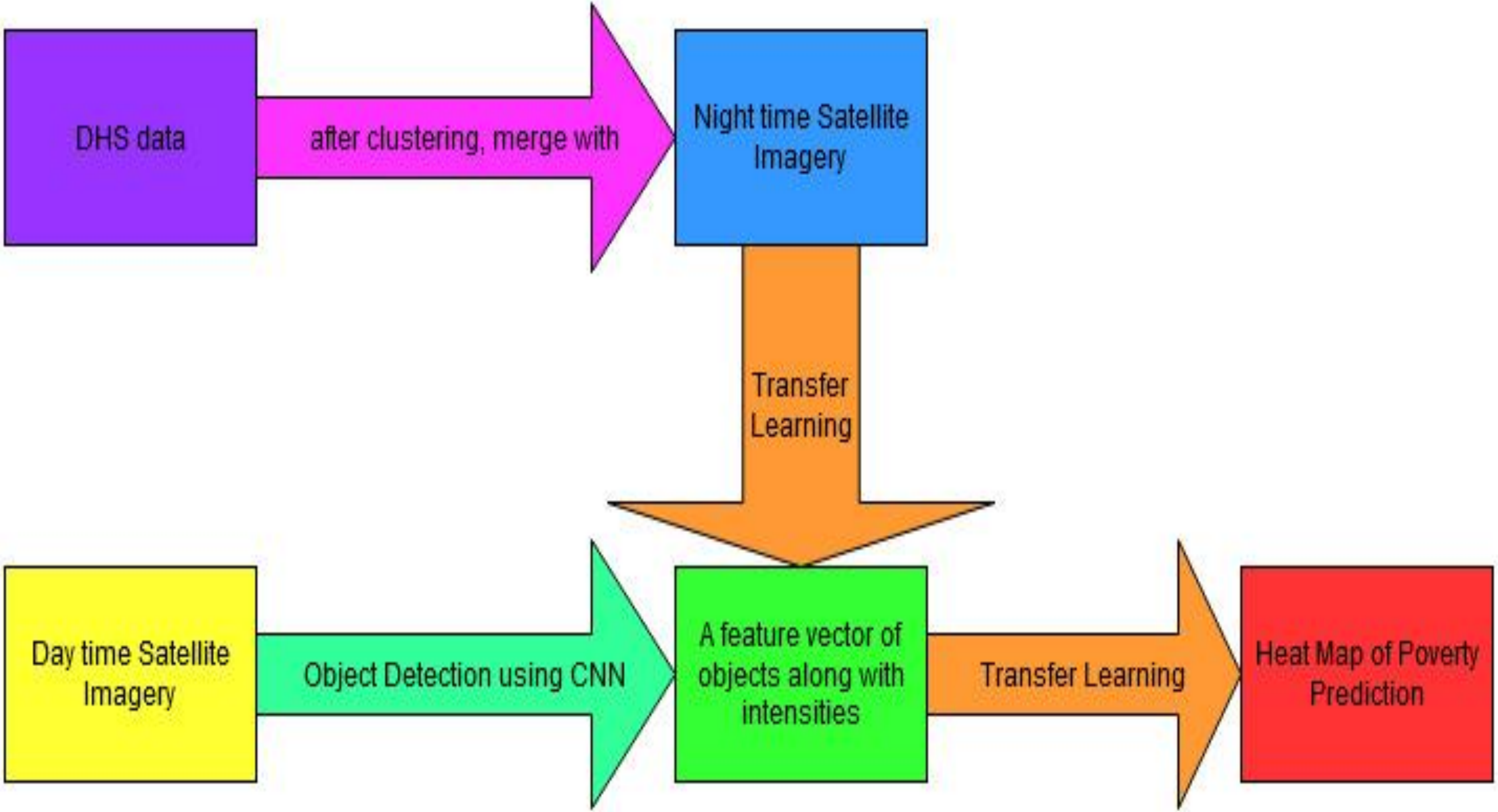
Data Collection

1. **Demographic and Health Surveys (DHS)** are nationally-representative household surveys that provide data for a wide range of monitoring and impact evaluation indicators in the areas of population, health, and nutrition. We took survey data of “Rwanda” country from this site. Rwanda is a small country in East Africa.

    a. This data contains clusterwise information about health and wealth.
    b. We also got the shape file for Rwanda from this site.

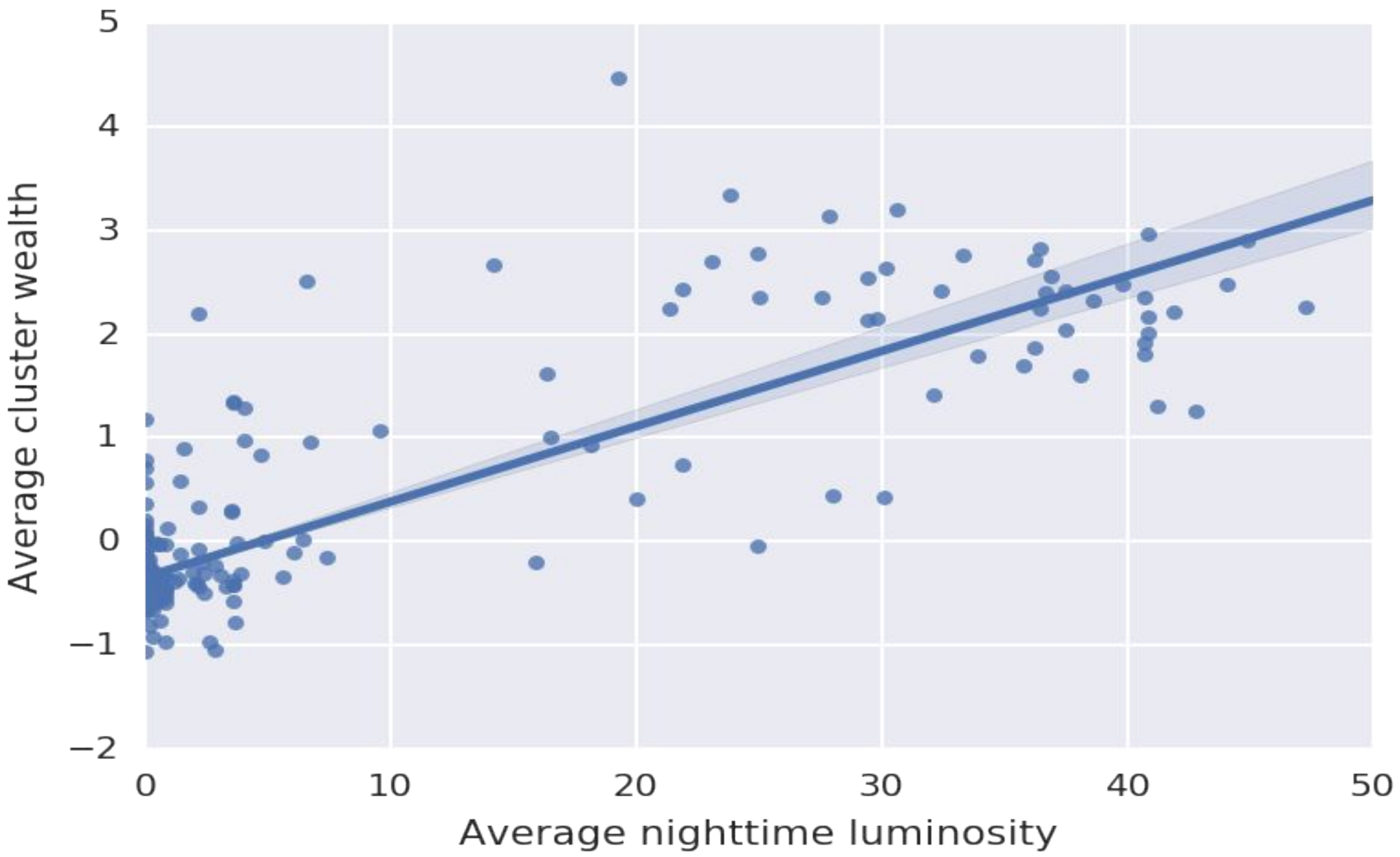
2. Nightlight image is from NOAA’s official site, which shows the average night luminosity of the world.

3. The Daytime Satellite Images were downloaded from Google Static Maps.


DHS data
after clustering, merge with
Night time Satellite Imagery
Transfer Learning
Day time Satellite Imagery
Object Detection using CNN
A feature vector of objects along with intensities
Transfer Learning
Heat Map of Poverty Prediction

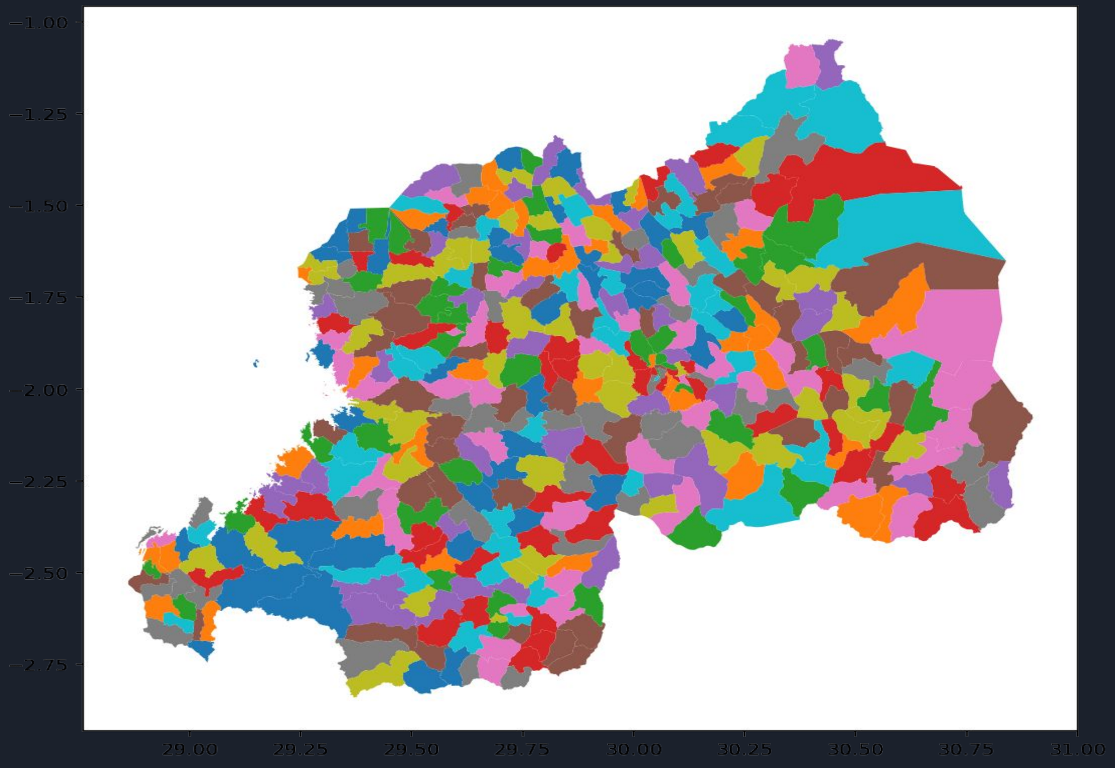
Code Flow

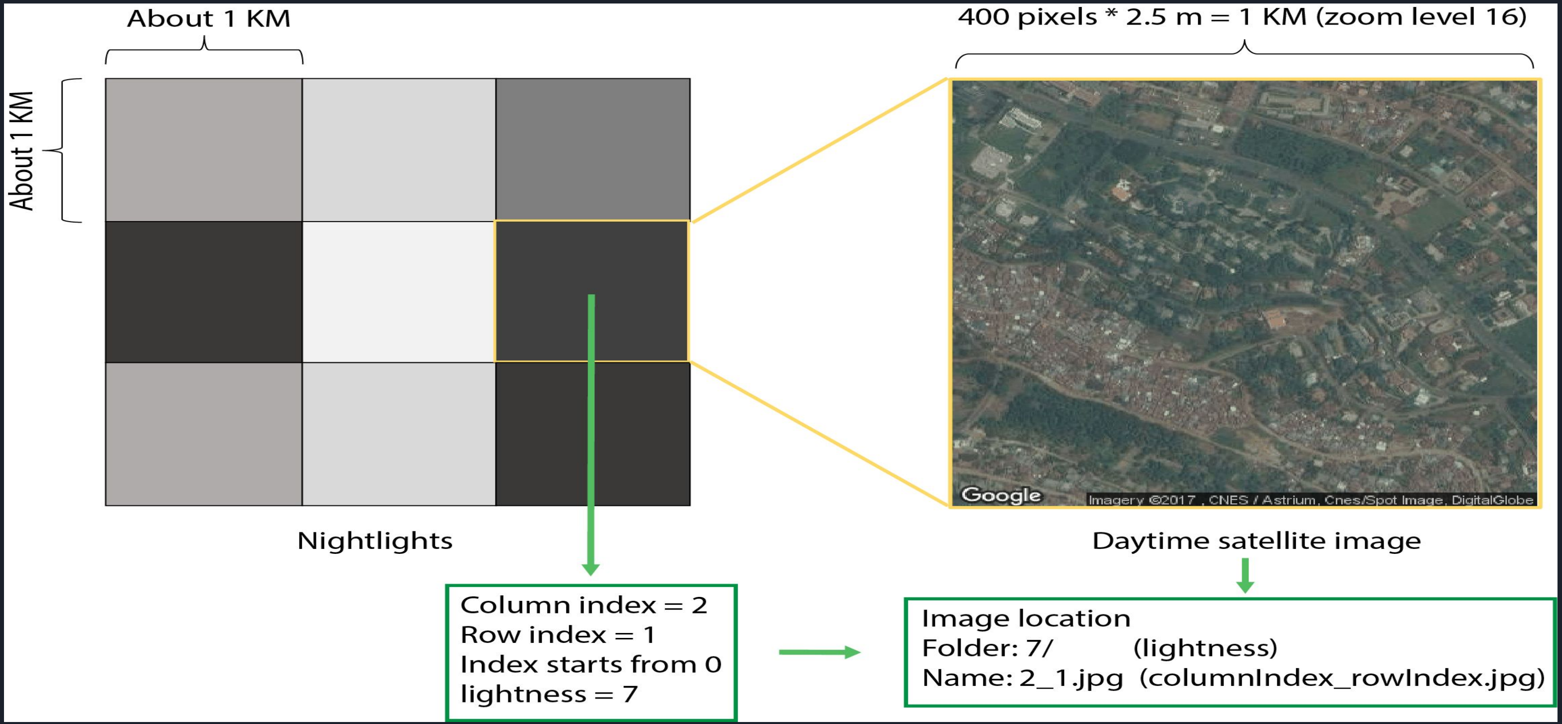
1. From the DHS survey data, we only kept the required information of cluster coordinates and took median of the wealth of that cluster area then stored that in a csv file. (Let’s name it DHS file).
2. The nightlight raster file is processed and the information about bands and coordinates values of corners and centroid is stored. Here we are using gdal library which is widely used in geospatial data processing.
3. Then we merge the nightlight image’s “Basic” features in our DHS file (Let’s name it DHS_Nightlight file). This merged dataset contains six columns (one indicates average cluster wealth, 5 nightlights features max,min,mean,median, std.).



Average cluster wealth
Average nighttime luminosity
5
4
3
2
1
0
−1
−2
0
10
20
30
40
50

4. The model is then regularized using ridge regression.
5. We have downloaded the shape file of the Rwanda map. The shape file is used to get the borders and range of the map. The visualisation of that is as follows:





6. The daytime satellite images were downloaded using Rwanda's shapefile and map coordinates values from DHS file. These images were downloaded at zoom level 16 and each image is of 400*400 pixels and labeled with their clusters' lightness from the nightlight data. This lightness is ranging from 0 to 63.

7. Then we divided these images into the three groups with respect to their lightness.
   ([0, 3)-->Class 1, [3, 35)-->Class 2, [35, 64)-->Class 3).

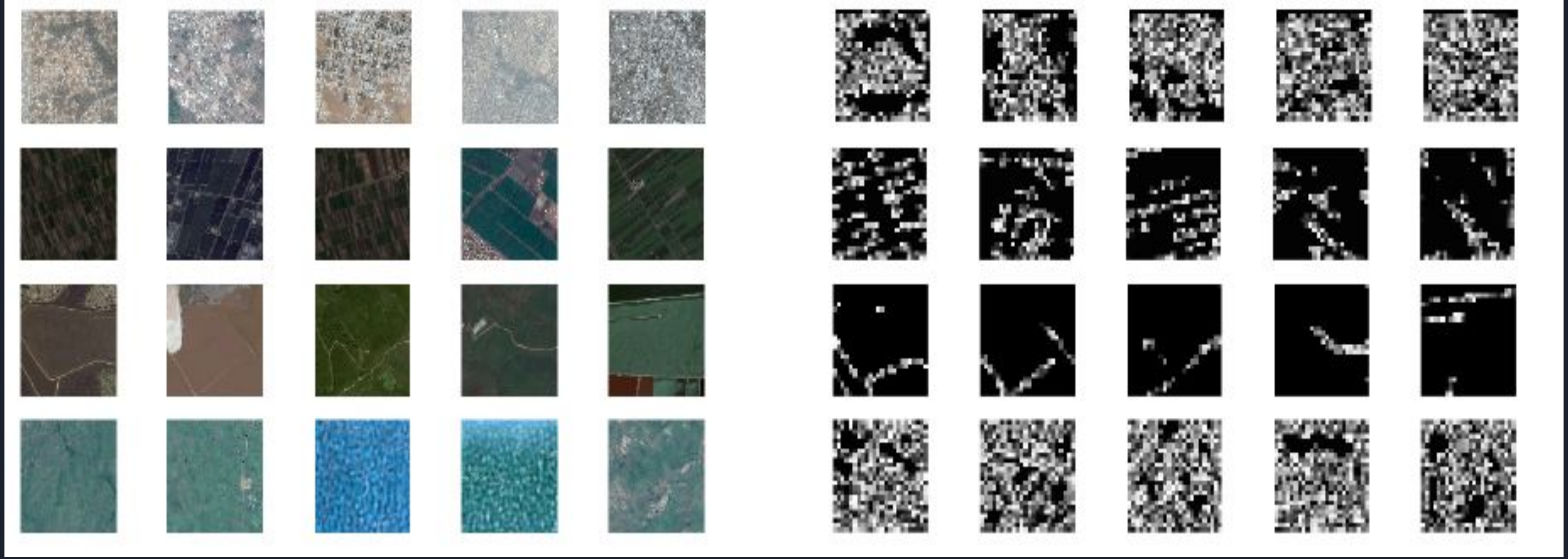
8. Now comes the most important step of our project.

★ We have daytime satellite images with label of its lightness class.

★ From these daytime images we extracted the features using VGG16 which has been pre-trained on the Imagenet.

★ Then we have retrained this model using the lightness labels.

★ So, the model has been trained on nightlights and also daytime images' features.

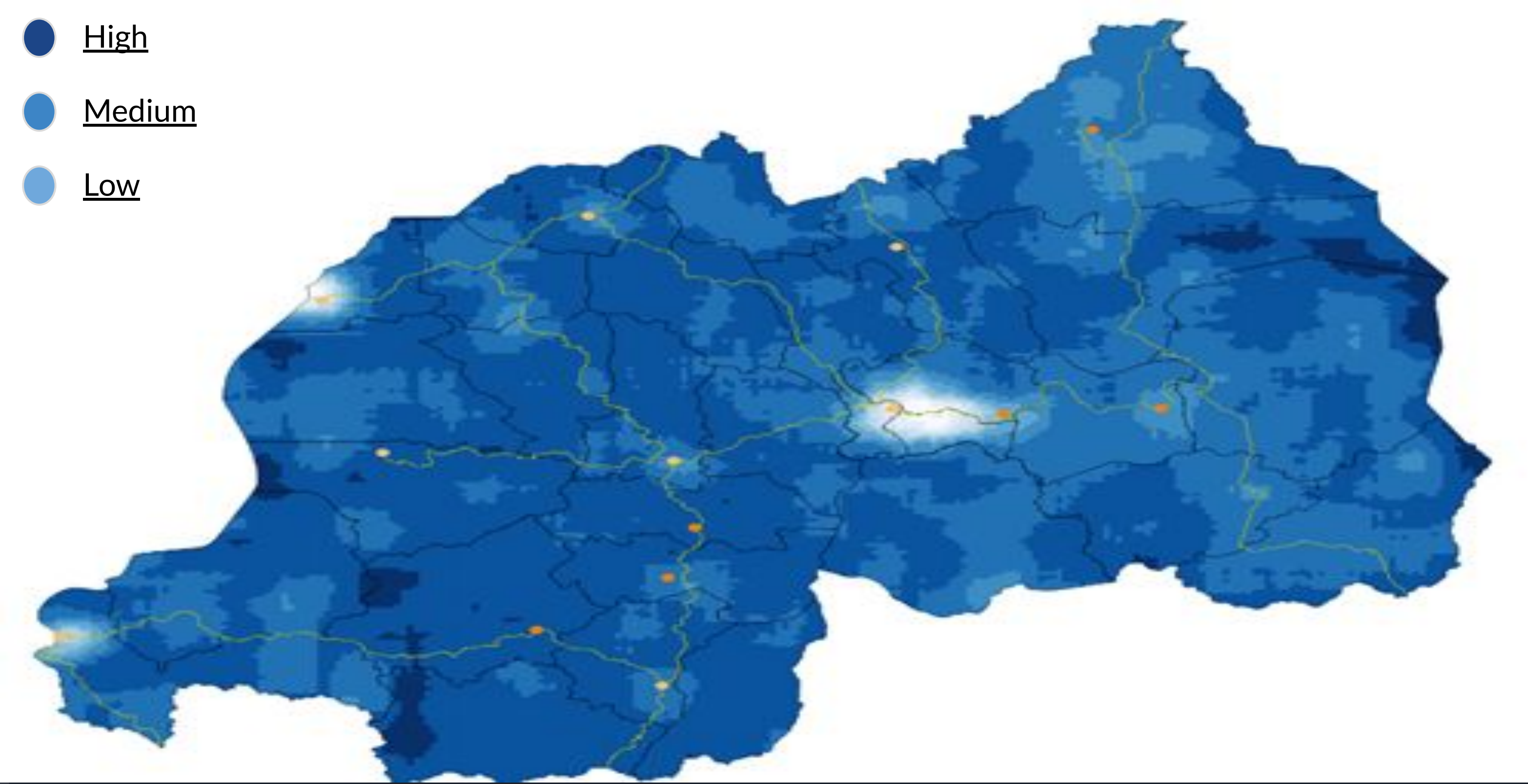


★ We can see that different daytime images activates different filters of our trained model.

★ Using these features we have predicted the wealth clusterwise as low (class 1), medium (class 2) or high (class 3). The model is then regularized using ridge regression.

★ The accuracy of the model in cross validation was 0.725

Final Output



Heatmap of clusterwise poverty

Conclusion

- Here, we introduce a new transfer learning approach for analyzing satellite imagery that leverages recent deep learning advances and multiple data-rich proxy tasks to learn high-level feature representations of satellite images.
- This knowledge is then transferred to data-poor tasks of interest in the spirit of transfer learning. We demonstrated an application of this idea in the context of poverty mapping and introduce a fully convolutional CNN model that, without explicit supervision, learns to identify complex features such as roads, urban areas, and various terrains.
- Using these features, we are able to approach the performance of data collected in the field for poverty estimation.
- Our approach can easily be generalized to other remote sensing tasks and has great potential to help solve global sustainability challenges.

References

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THANK YOU!!