## Predict Poverty by Satellite Imagery and Deep Learning

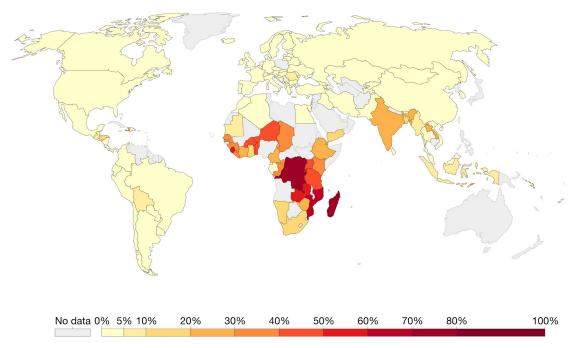
Chiyuan Cheng 08/2020

### sub-Saharan African countries are in extreme poverty

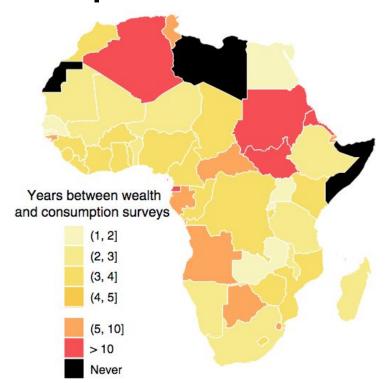
#### Share of the population living in extreme poverty, 2017

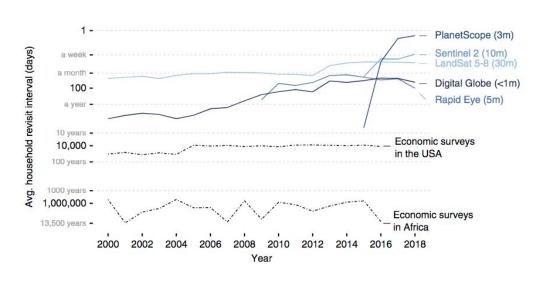


Extreme poverty is defined as living with per capita household consumption below 1.90 international dollars per day (in 2011 PPP prices). International dollars are adjusted for inflation and for price differences across countries.



## Economic data obtained from household surveys are infrequent in African





## **Objective**



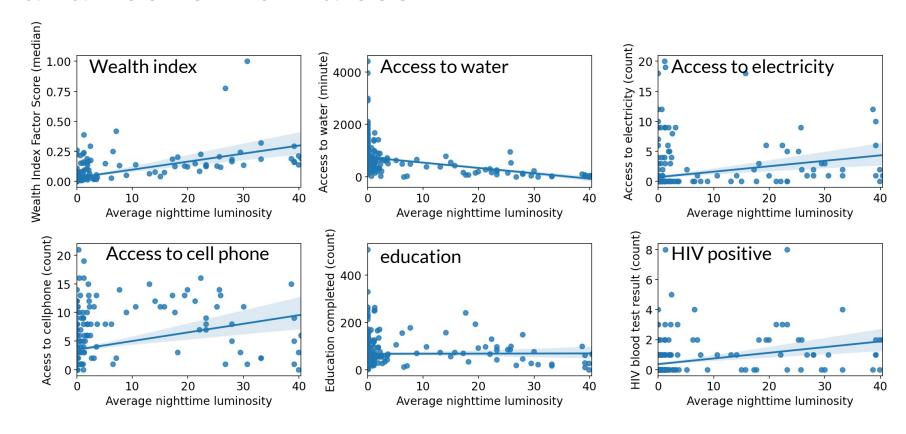
Burundi as an example

- The lack of reliable data in developing countries is a major obstacle to their economic development.
- Traditional methods to collect the poverty data by household surveys can be expensive and time-consuming.
- We aim to use the satellite imagery to estimate the socioeconomic variables in a specific country using deep learning and computer vision

#### **Data source**

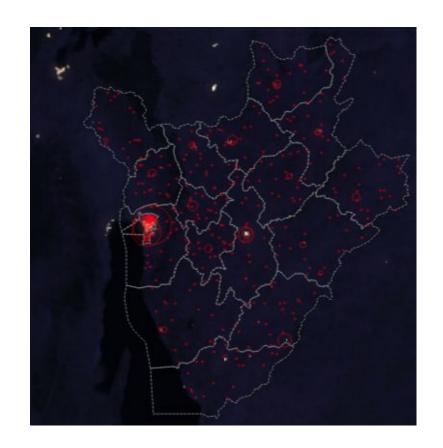
- Demographic and Health Survey (DHS) data
  - o 2010 Burundi DHS
  - $\circ$  Use "Wealth Index" to measure the well-being.
- Satellite image (nighttime): NOAA
  - o Burundi 2010 was downloaded from NOAA.
  - o The image includes a luminosity level from 0 to 63
- Satellite image (daytime): Google map API
  - Image size = 400 pixels x 400 pixels (1 pixel = 2.5km)
  - $\circ$  Total images = 50,000

# Relationship between Nighttime Luminosity and Economic Indices

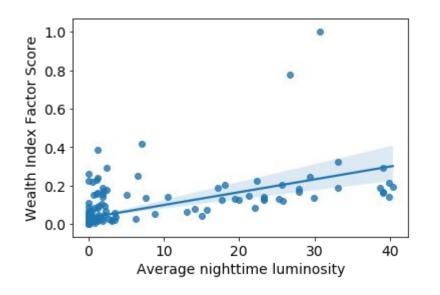


## Wealth index overlaid on the nighttime imagery

- DHS data contains in different 376 clusters with longitude and latitude
- Merge light intensity (luminosity) from satellite image with DHS data and group by with the mean value of luminosity for each cluster
- 73% of area in the nightitme imagery are dark (luminosity = 0)



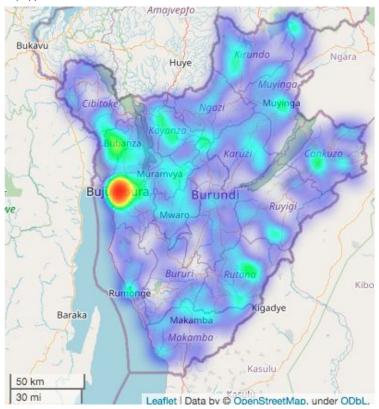
# Regression models: Predict wealth index from luminosity



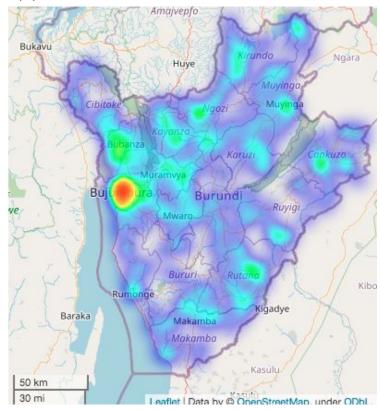
model	R <sup>2</sup>
Linear regression	0.50
Lasso	0.50
Rigid	0.50
Random forest	0.54

## Predict wealth index from luminosity

(a)) Ground-true wealth index index



(b) Predicted wealth index



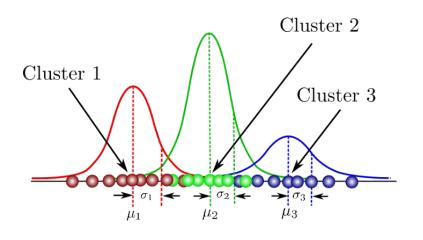
## Classify daytime satellite imagery with luminosity by Gaussian mixture Model

#### <u>luminosity</u>

(a) High (10-63)



Gaussian Mixture Model



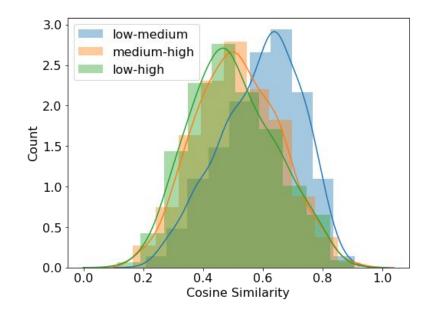
(b) Median (1-9)





(c) Low (0)

# Pairwise similarity on satellite imagery



#### <u>luminosity</u>

(a) High (10-63)



(b) Median (1-9)

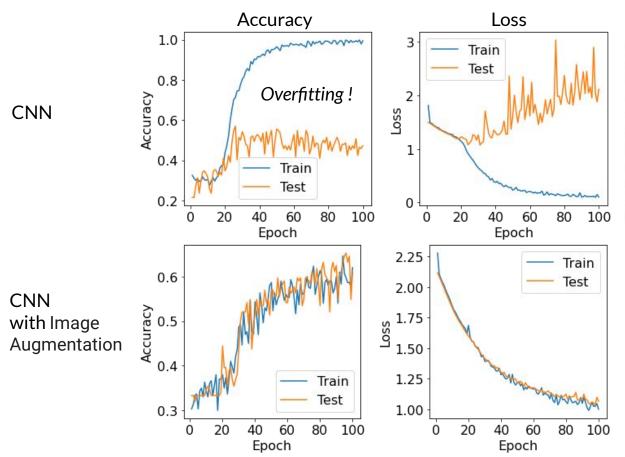


(c) Low (0)





### **CNN** model



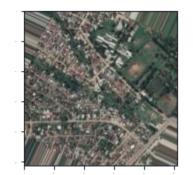
Layer (type)	Output	Shape	Param #
conv2d_8 (Conv2D)	(None,	254, 254, 32)	896
conv2d_9 (Conv2D)	(None,	252, 252, 64)	18496
max_pooling2d_5 (MaxPooling2	(None,	126, 126, 64)	0
dropout_12 (Dropout)	(None,	126, 126, 64)	0
flatten_5 (Flatten)	(None,	1016064)	0
dense_12 (Dense)	(None,	128)	130056320
dropout_13 (Dropout)	(None,	128)	0
dense 13 (Dense)	(None,	3)	387

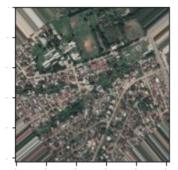
Total params: 130,076,099
Trainable params: 130,076,099
Non-trainable params: 0

## Image augmentation to avoid overfitting



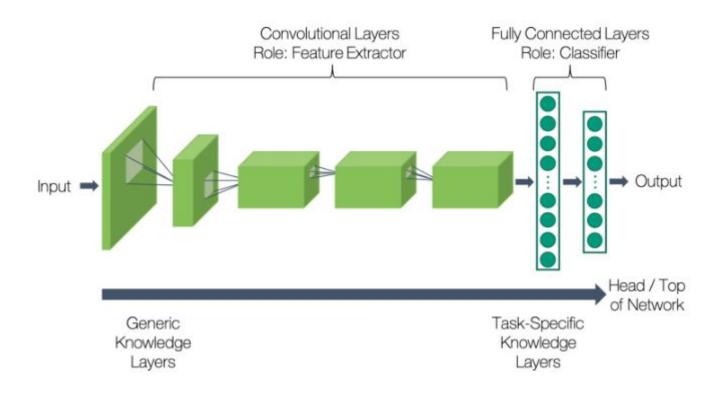




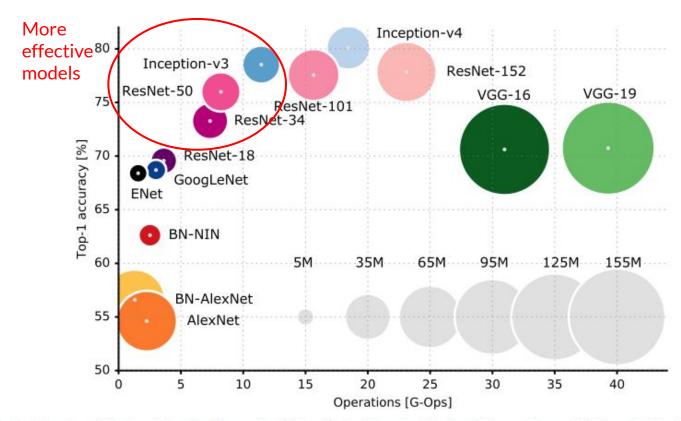




## **Transfer Learning (VGG16)**

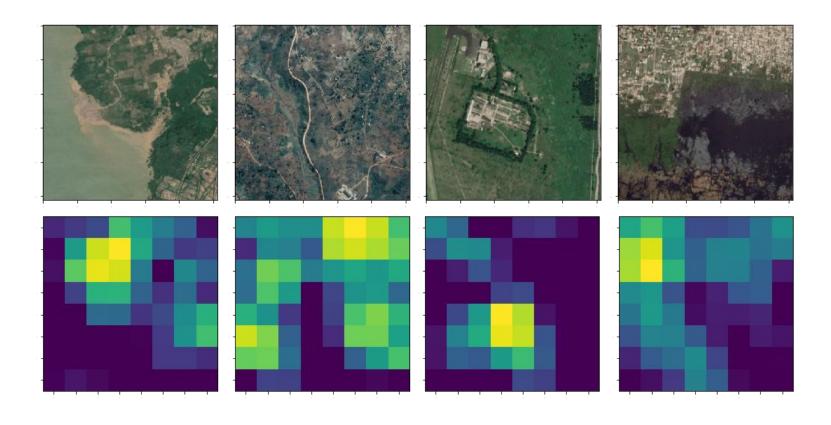


## Model performance of pre-trained models

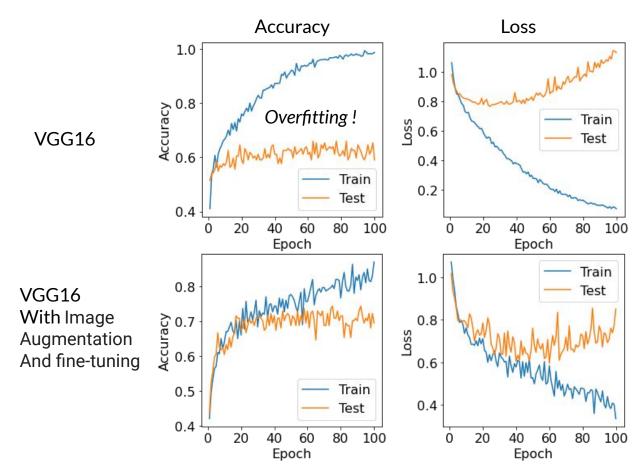


Alfredo Canziani, Adam Paszke, Eugenio Culurciello, "An Analysis of Deep Neural Network Models for Practical Applications"

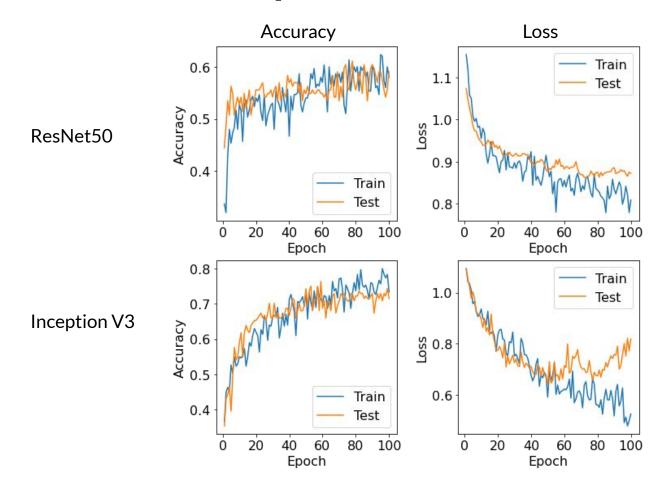
### **Feature extraction (VGG16)**



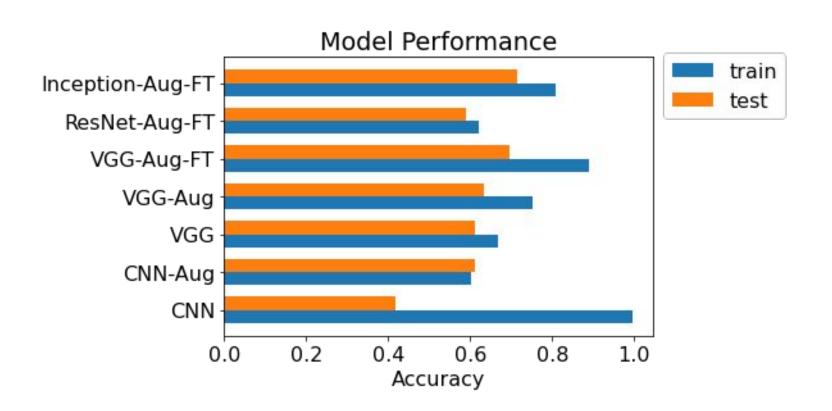
## **Transfer Learning (VGG)**



## More effective pre-trained models



## Model performance



### Conclusion

- Transfer learning and deep learning with satellite imagery can implement to capture the feature of satellite imagery to predict economic activities in developing countries, with the best model achieving 80% accuracy.
- We confirm the applicability of this method to predict wealth index using luminosity from nighttime satellite imagery, with the best regression model achieving R2 of 0.54.
- This method opens up unique opportunities to predict local economic indicators over time in developing countries, which typically requires expensive household surveys.