

Using Satellite Imagery to Predict Level of Poverty and Education in Haiti, Nepal, and Rwanda

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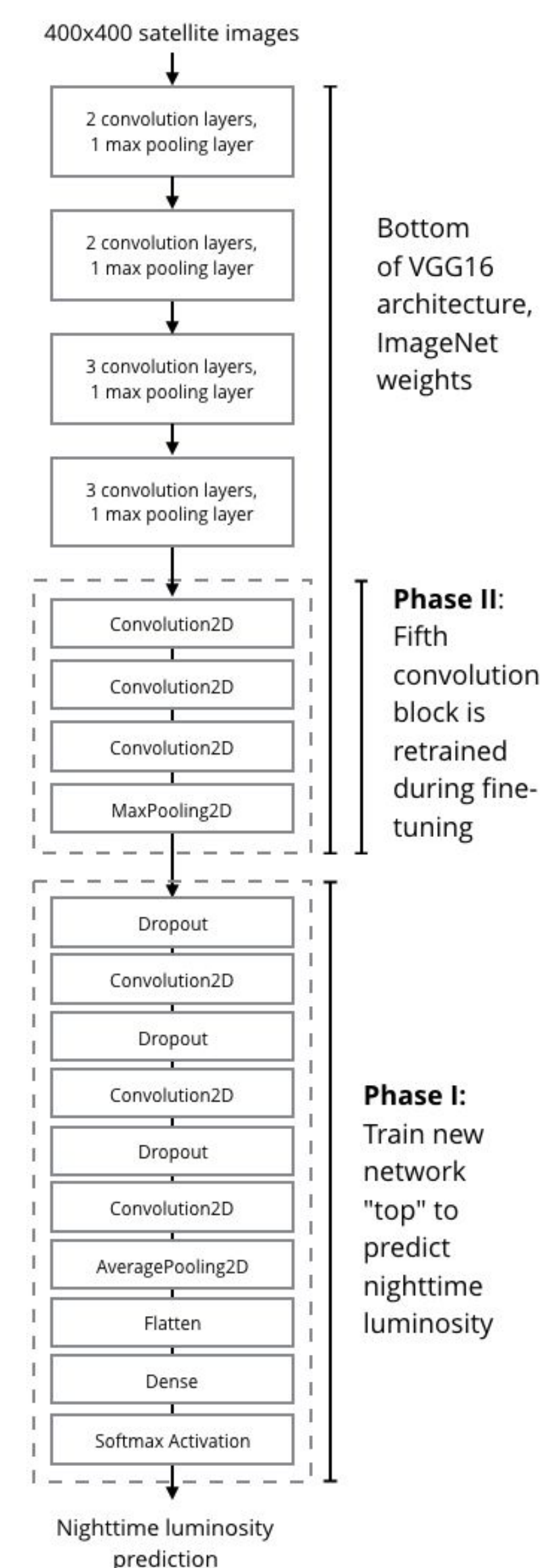
Describing Development, Beyond Wealth and East Africa

We explore the extent to which satellite images can predict:

- Poverty in countries *beyond East Africa*, like Haiti (Americas) and Nepal (Southeast Asia)
- Residents' level of education

Our aim is to further the potential of prior techniques that predict wealth in East Africa using satellite images.

Our Transfer Learning Process

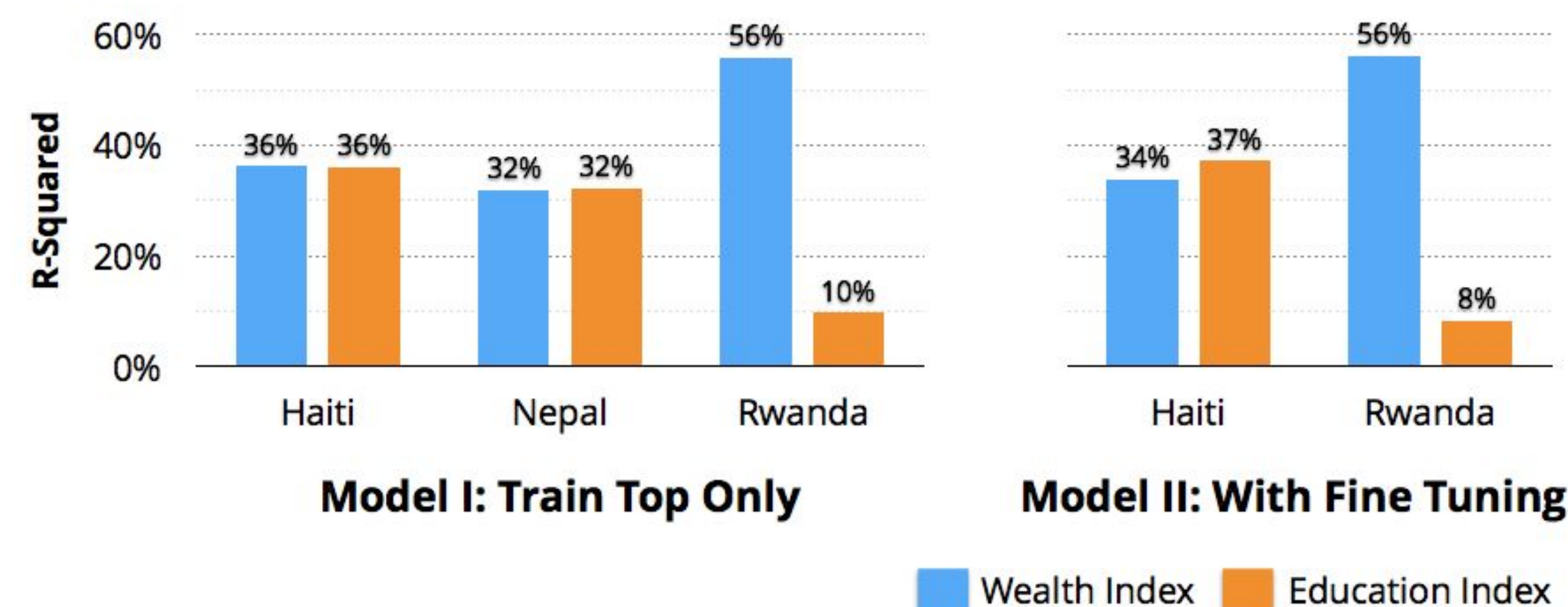


We predict wealth and education indexes from satellite images with a two-step transfer learning process. This includes:

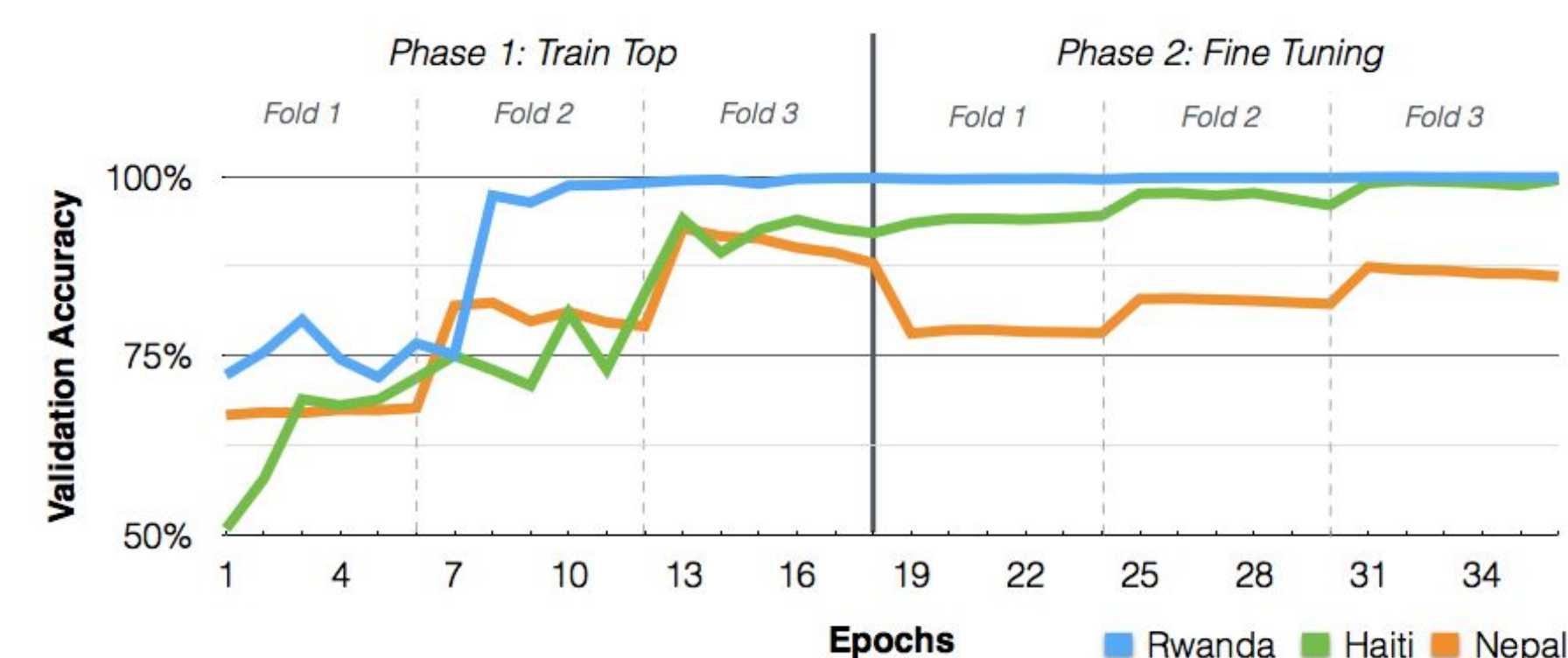
- A neural network (*left*) trained in two steps, that predicts night-time luminosity from satellite images.
- A regression model that predicts wealth and education indexes from DHS surveys using high-level features from the network.

Predictions Weaken Beyond Rwanda and Wealth

All experimental models for Haiti and Nepal and for education level **performed worse than the model we trained to predict wealth index in Rwanda**. Follow-up analyses revealed two reasons the new models did not achieve comparable performance.

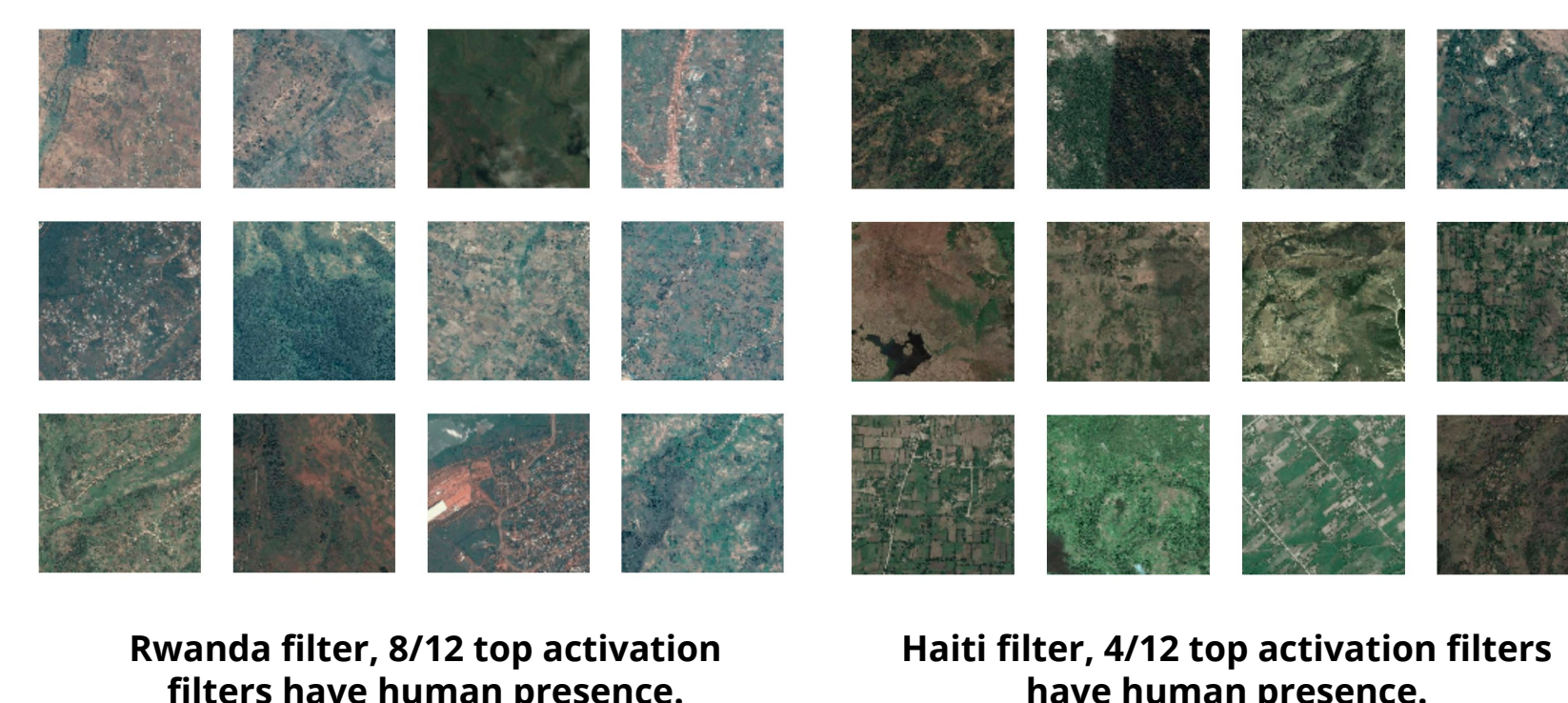


Diagnosis 1: Satellite Images Describe Nighttime Luminosity Less Outside Rwanda

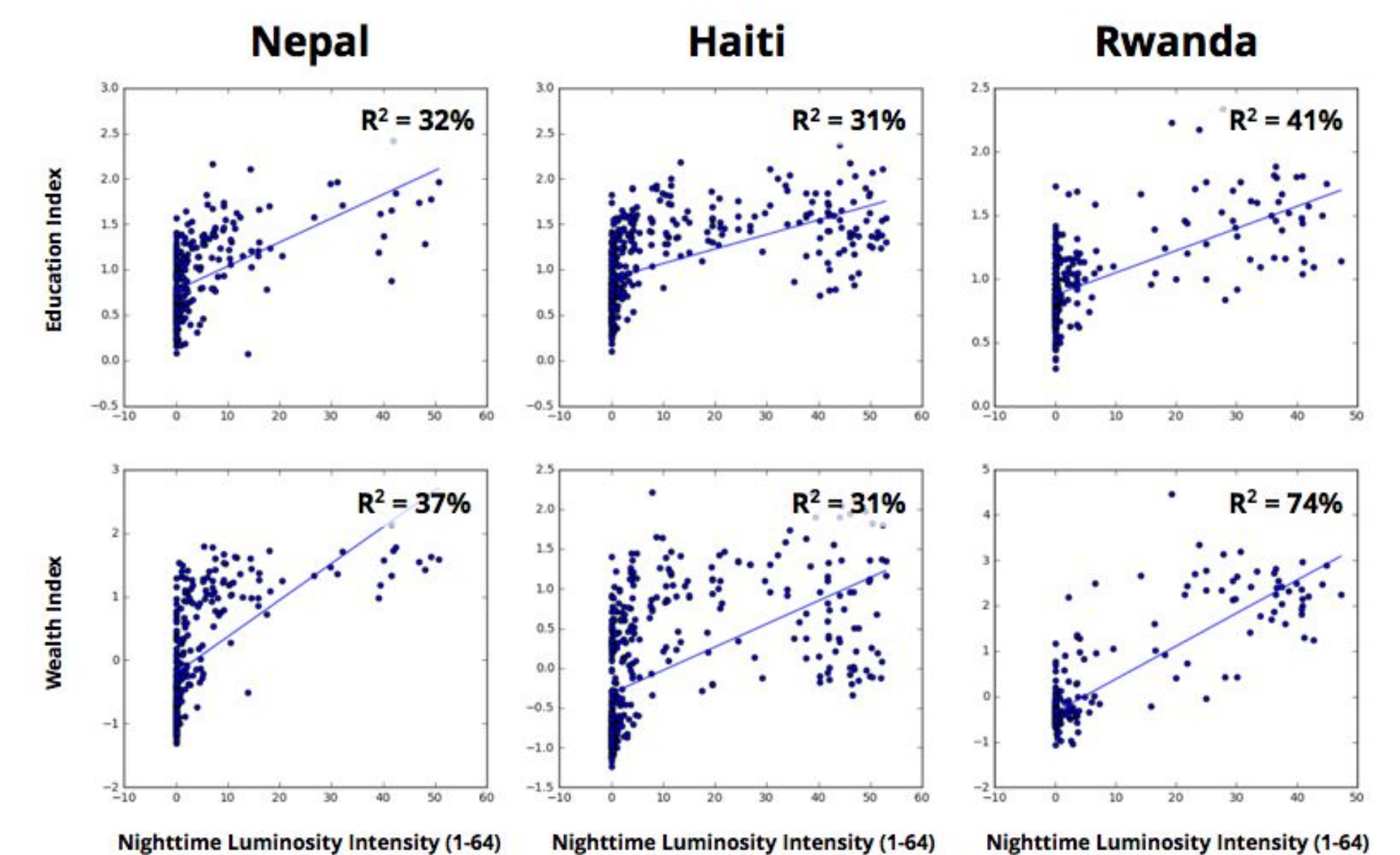


Rwanda's model reached >95% validation accuracy within a rapid 8 epochs of training.

Some filters in the Rwanda model had obvious human presence. For Haiti, such filters were rarer and less "pure".



Diagnosis 2: Weak Relationship Between Nighttime Luminosity and Economic Measurements in Some Countries



Luminosity isn't a strong proxy for all economic measurements in all countries.

Additional Methods

Education index: DHS survey data includes the level of education for each household. We cast no education, primary, secondary, and higher education to an ordinal scale from 0-3, and average this measure within each cluster.

Looking Forward

Further study can confirm whether more training can remedy poor performance, and characterize the gamut of countries for which visual features related to economic well-being are difficult to learn.

Acknowledgments

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