Socio-Economic Wealth Analysis Using Satellite Feature Imagery

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Introduction

The proposed work aims to use Convolutional Neural Networks along with satellite imagery to analyse the wealth conditions of a given geographical location. Furthermore, it aims at replacing the traditional review-based approach for conducting poverty analysis, thereby allowing governments and Not-for-Profits to launch development schemes in prioritised areas.

Motivation

The elimination of poverty worldwide is the first of the 17 UN Sustainable Development Goals for the year 2030. To track progress towards this goal, there is a need for frequent and more reliable data on the distribution of poverty. The proposed work uses an image feature vector to perform such analysis of the distribution at a highly reduced cost.

SCOPE of the Project

The economic estimations are based on features derived from satellite images such as roof type, vegetation, demography and nightlights. The estimation depends on a scale as defined by Variants of the Multidimensional Poverty Index. The following components are composed of feature detection, night light estimation, poverty calculation using DeWalle's formulation.

Methodology

The following model uses Neural Networks to provide a model for enhanced analysis of the given problem statement. The model is trained using convolutional neural network is LSTM for image features. Satellite image data from several sources were collected. The Data was taken as a 1x1 km satellite image from various areas. The images were available in both 3 band and 16band. The multi-band images are obtained from the multispectral (400 – 1040nm) and short-wave infrared (SWIR) (1195-2365nm) range. We select the appropriate unit and weight for the measurement.

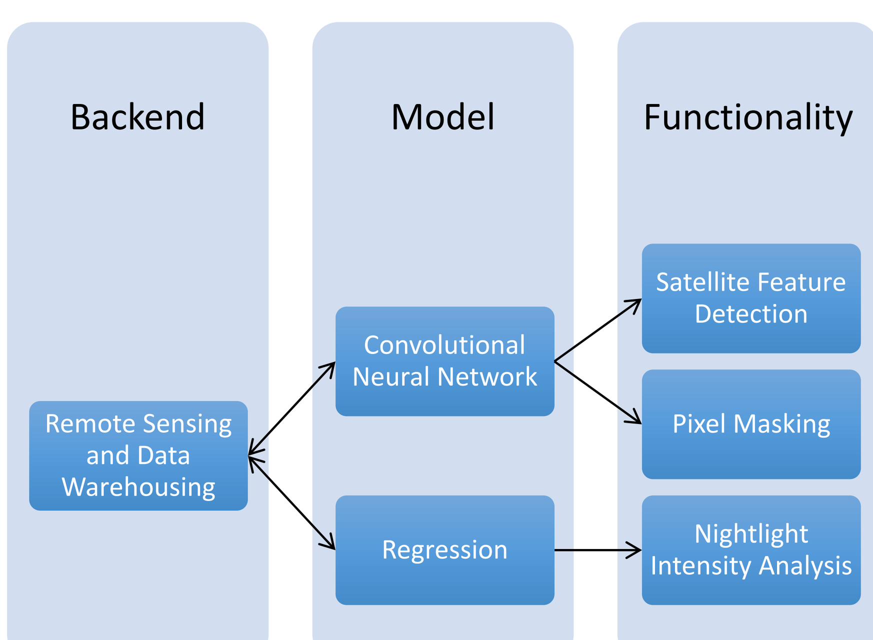


Figure 1: System Architecture

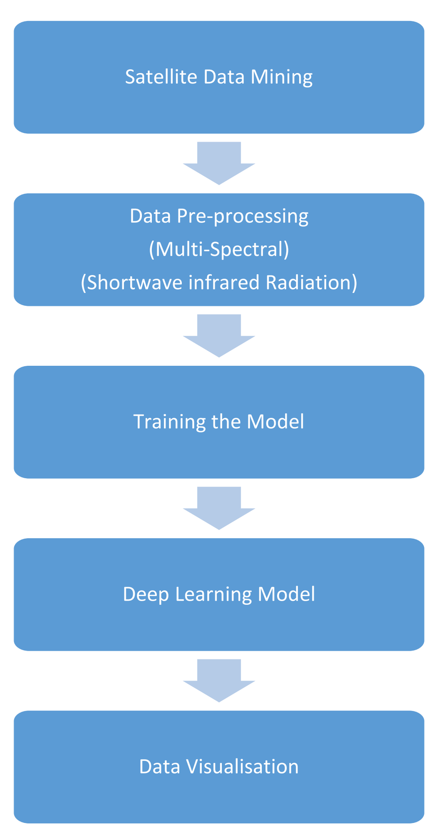


Figure 2: Flow of Execution

An indication factor i is coupled with weight w in order to estimate the final robust figure. We use the indicator component i to compute specific elements w_i for the metric.

$$\sum_{i=1}^{d} w(i) = 1$$

$$\ln Z_i = 6.704 - 1.773 \ln \left(\frac{C}{cap}\right) + 0.228 \left[\ln \left(\frac{C}{cap}\right) \right]^2 + v_i$$

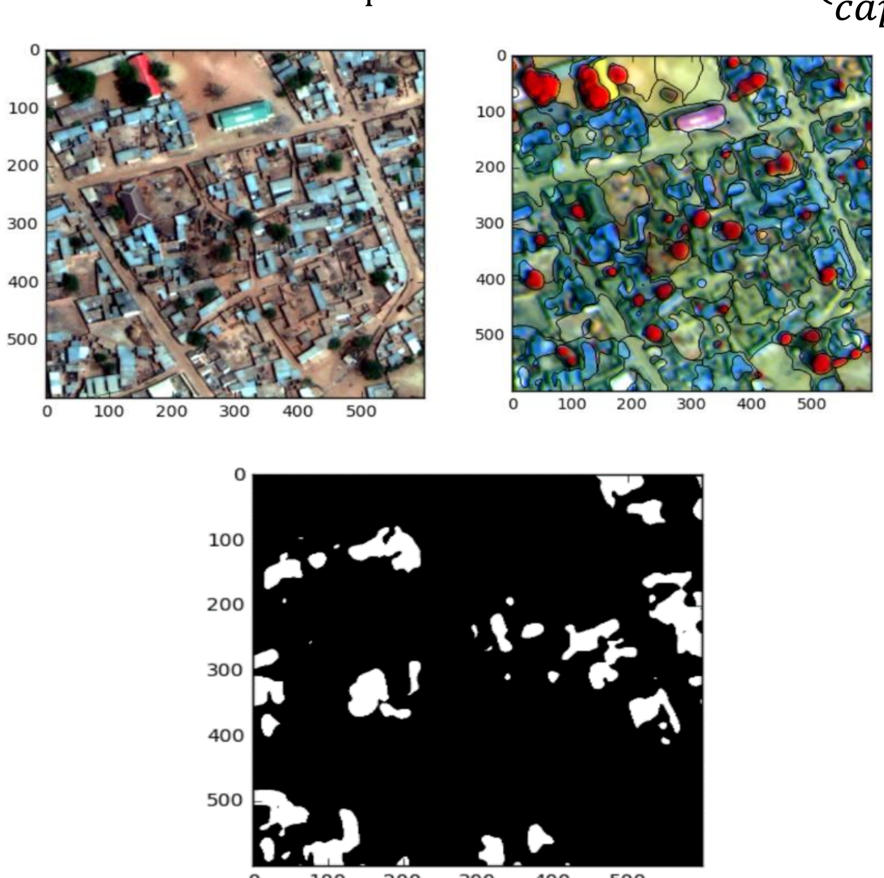


Figure 3: Feature Isolation for Man-Made Structures

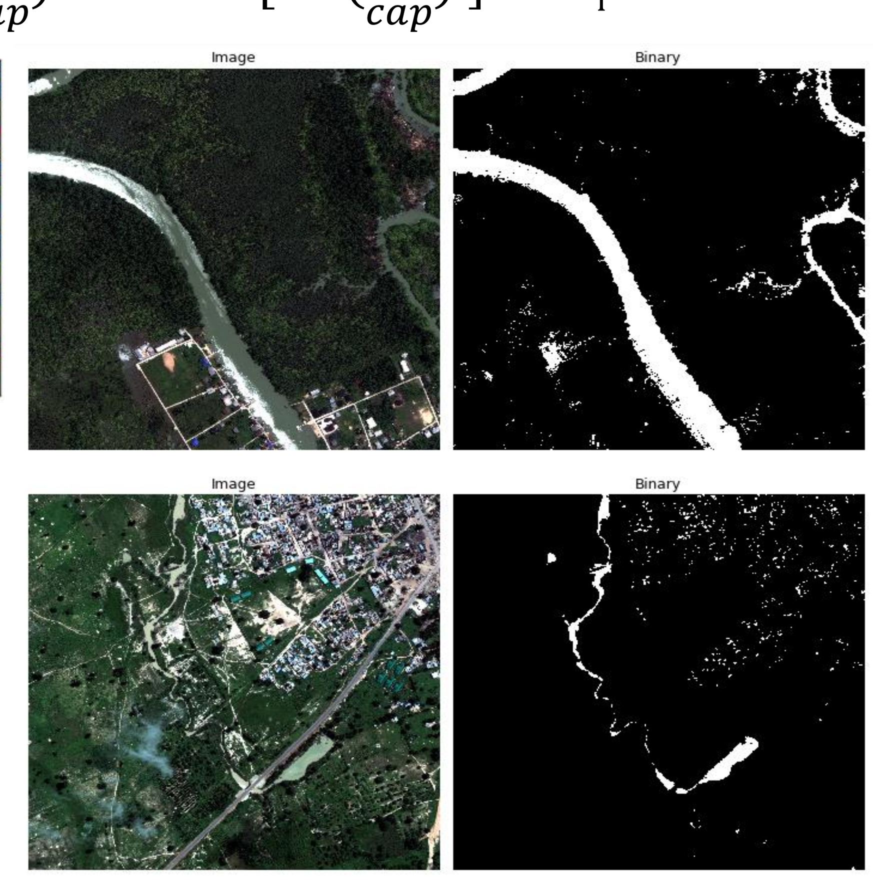
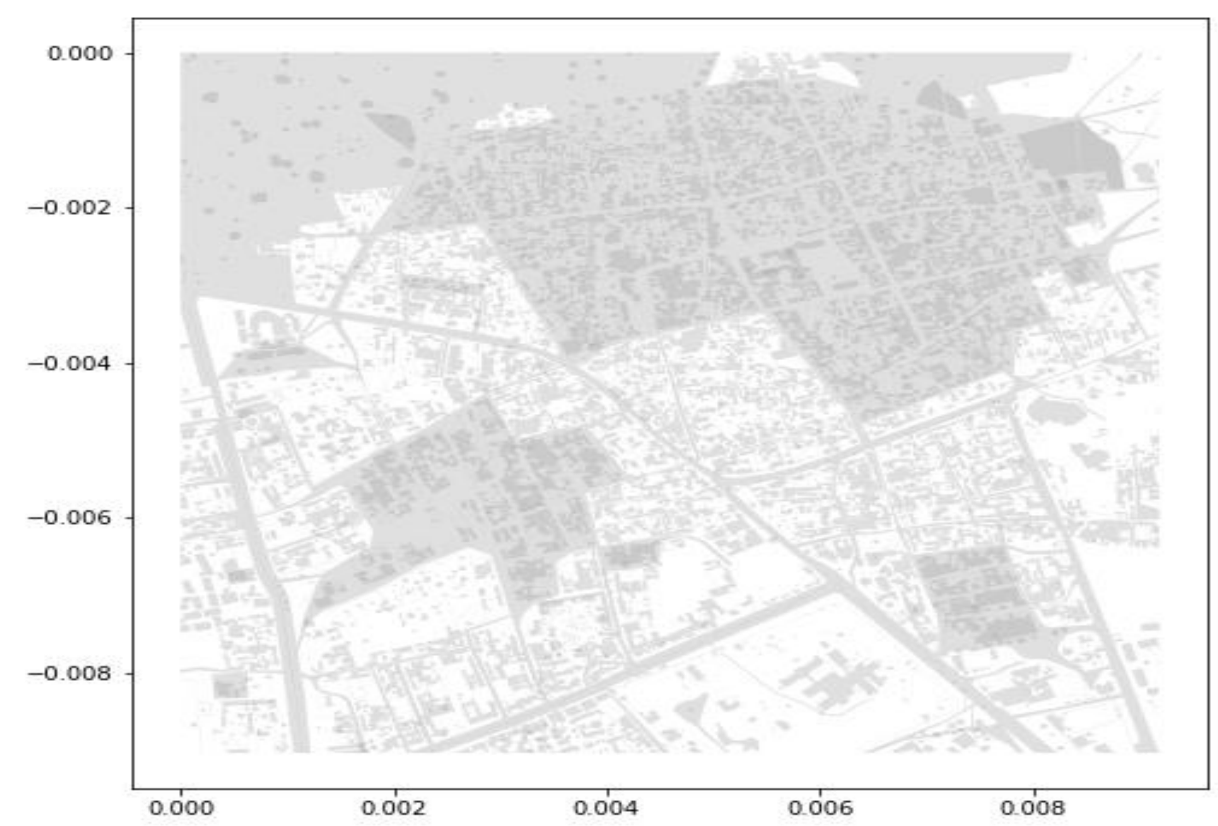


Figure 4: Isolation of waterbodies and vegetation

In this dataset that, we make a lot of geo-arranges that are in the scope of x = [0,1] and y = [-1,0]. We used a convolutional neural network with 16 inputs for modelling our problem. We combined the satellite imagery to train a classifier that can isolate features in a satellite image based on classes. We also use a logistic regression to train a pixel-based classifier and estimate the similarity of features using Jaccard measure of similarity. The figure 1a was fed to the classifier for isolation of features.

Results

The neural network was executed for various test images in order to computer poverty measures and detect the various features available. We also implemented the nightlight poverty estimation measure in order to draw a comparison between the methods of feature-based poverty estimation and nightlight-based poverty estimation. When we are able to generate a final poverty score for the different measures, the final problem reduces to a regression problem. Hence, by using the different regression techniques we have established a direct correlation between nightlight and poverty. Similarly, we now use the satellite image features in order to compute the final poverty status. We use the formula defined in section III in order to compute the same. We used the weights obtained after training our CNN. The image is coloured differently based on the various features. Areas with dark features tend to have a higher income index and man-made features compared to those which are whiter. The features are divided into 10 classes as follows:-



```
Type:    1, objects: 1962
Type:    2, objects: 3201
Type:    3, objects: 1
Type:    4, objects: 33
Type:    5, objects: 1452
Type:    6, objects: 20
Type:    7, objects: 0
Type:    8, objects: 6
Type:    9, objects: 9
Type:   10, objects: 548
```

Figure 6: Feature Count Matrix

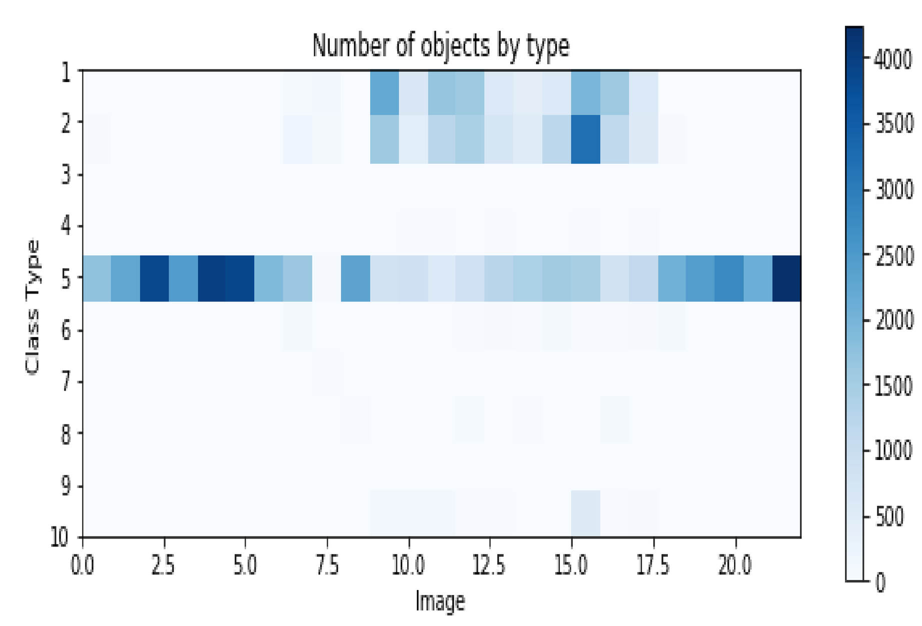


Figure 7: Class based segmentation

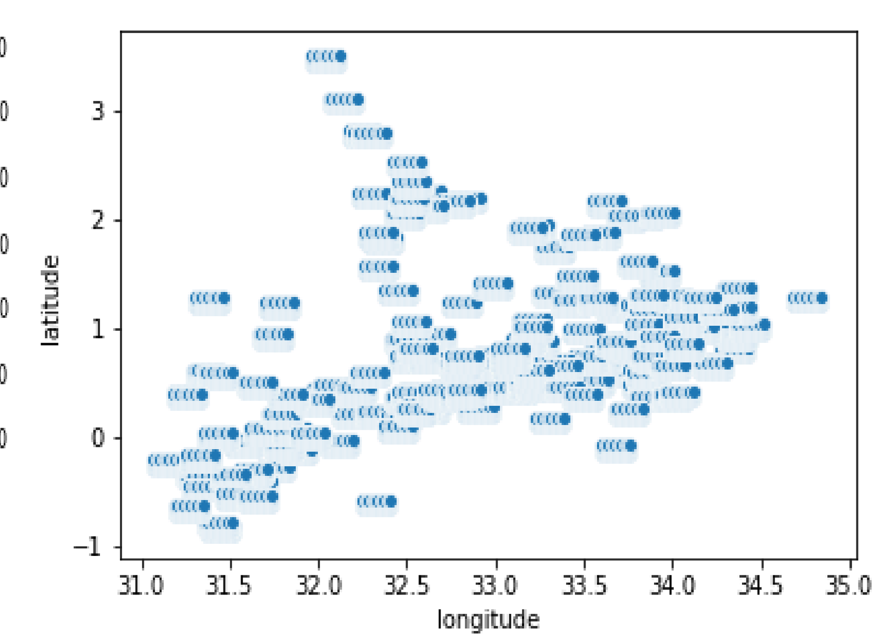


Figure 8: Variation of coordinates with nightlight intensity

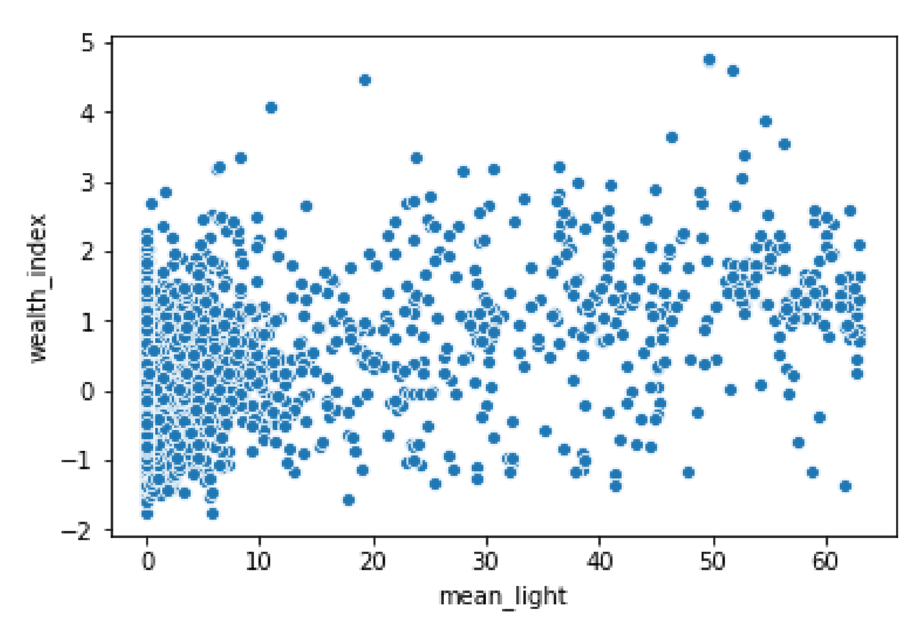


Figure 9: Wealth Index vs Mean Light

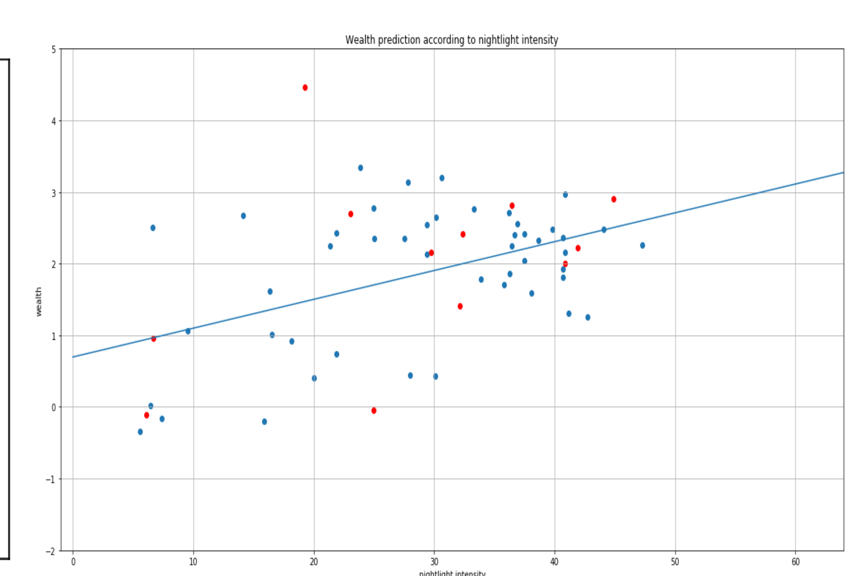


Figure 10; Regression Model Nightlight vs Wealth

Conclusion

Our predictions for utilization consumptions approach review exactness, while our predictions for wealth put together would be an improvement over the already existing algorithm. Moreover, our poverty estimation procedures dependent on remote detecting and AI can be connected on a worldwide scale at a part of the expense of conventional review-based strategies. Inexpensively and precisely anticipating destitution in developing nations can support governments and non-benefits better apportion their assets and make successful strategies. The algorithm achieved an overall efficiency of 72% which is comparatively higher than previously available methods.

References

[1] Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., & Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. Science, 353(6301), 790-794.

[2] Weidmann, N. B., & Schutte, S. (2017). Using night light emissions for the prediction of local wealth. Journal of Peace Research, 54(2), 125-140.

[3] Ogneva-Himmelberger, Y., Pearsall, H., & Rakshit, R. (2009). Concrete evidence & geographically weighted regression: A regional analysis of wealth and the land cover in Massachusetts. Applied Geography, 29(4), 478-487.