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Predicting Poverty Index on Satellite Images & DHS Data using Transfer Learning

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Abstract:

For economic livelihood, reliable information remains skimp in the developing world. Poverty is one of the seventeen sustainable development goal to be get removed as mentioned by the United Nations. In the earlier times, the primary source of data to measure poverty is ground-level survey data such as household consumption and wealth. With the advancement of technology, among different approaches that are available the one adopted by the developed or developing countries is to estimate the poverty index of an area using remote sensing data such as satellite images using machine learning technique. The source of data used in this approach is highly structured, inexpensive and easily available. This machine learning technique not only estimates the poverty index of a year, but also establishes the relationship of index between the years. Our proposed approach uses pre-trained Inception Net_V3 to predict the nightlight intensity corresponding to input daytime satellite images. The proposed model also predicts the cluster wealth score and established the correlation between wealthscore obtained from Demographic and Health Survey (DHS) data and Satellite Images i.e. r value (Pearson Correlation Coefficient)

Keywords: Convolutional Neural Network, Demographic and Health Survey, Inception_V3, Transfer Learning

I. INTRODUCTION

After 70 years of Independence, India is one of the fastest growing nation in the world. India's GDP has reached $ 2.93 Trillion in 2019 estimations which shows its tremendous growth in these 70 years. But after all these developments, the matter of concern and major problem in the Independent India is Poverty [17]. UN has also included Poverty in the seventeen sustainable development goals to be removed till 2030. The major problem with India's Development is - The major part of Indian Society is untouched with the benefits of development. It is rightly said that "if economic growth is not shared among the society, the development will be failed". The poverty rate has certainly been improved as compare to the rate that had been at the time of Independence. But despite of running several programs and implementing different policies by the government to alleviate poverty, our country lacks when it comes to measure the poverty rate at global level. The difference among the opinions of economists and intellectual also led to the chaos in the country regarding poverty estimations. India lacks the uniform methodology to estimate the poverty. Poverty refers to a condition where a person lacks basic amenities, financially and non-financially to satisfy the human needs [18]. In order to estimate the poverty index, the one and only data we have used till data is Survey Data, which is not accurate, expensive method of data collection and time consuming. In the last years, the huge amount of remote sensing data, combined with machine learning techniques, led to methods for estimating socio-economic indicators such as satellite images. In particular, such method overcome the lack of data and estimate the poverty at large scale in developing countries. The method has successfully got implemented in several African countries and gave better output when compared with the manual effort. In this paper, we have observed survey data and satellite images and compared the results obtained from both the methods. It has been observed that our approach using satellite images gave the better result or better accuracy when compare with the survey data in minimal time and cost. This technique can also be adopted by the government with the eye on Digital India where everything is calculated online. The method will reduce the gap in the data and assist to understand poverty in regions which helps in creating policy to allocate resources [19]. The results obtained can be provided to different policy makers and government agencies for further development. The basic of the research includes the study in which the similar pretrained model is used and poverty is estimate of the particular region using the cluster wealthscore.

II. LITERATURE SURVEY

Reliable information for predicting poverty remain unavailable in the world now. This is due to the dearth of data regarding the social, environment, and health and livelihood issues [6]. Rich countries have large amount of data to measure the poverty, but developing countries lack with spatially sparse and infrequently collected data due to high cost of surveys. Poverty, a major agitation, has also been mentioned as the first of seventeen Sustainable Development Goal by the United Nations to get removed [7]. In the earlier times, the primary source of data to measure the poverty is the ground-level survey such as household consumption and wealth, which is time consuming, expensive and inexact source of data [8]. In the context of Ground Level Surveys, LSMS (Living Standard Measurement Survey) was initially used. LSMS survey is used to calculate the Household Expenditure. Since the scope of LSMS survey is very small, it does not provide the wealth of information [9] [10]. Using mobile data, digital footprints is an attempt to predict the poverty. To track the progress of the Sustainable Development Goals and target the intermediate information requires persistent, versant on economic, ecosystem and livelihood conditions. Remote Sensing data such as satellite imagery is becoming easily available and inexpensive, the data gathered from the satellite images is highly structured. The goal of this is to minimize the data gap using publicly available data source, for this a CNN is to be trained to estimate the poverty level using satellite imagery [11] [12]. These Machine Learning approaches not only estimate the poverty level for a single year but also establishes the relationship between several years. The foremost goal of the study is to spontaneously learn visual features in satellite images that indicates the poverty in a region. The techniques also suggest that predicting poverty from multiple developmental parameter is more reliable than predicting poverty from a single parameter. Satellite Imagery is used for Object Identification, Image Segmentation and Labelling of an Image. High resolution Google Static Maps Imagery is used, but since Google Static is exclusive, a low resolution image can be used [1]. Publicly available satellite imagery can be taken from the United States Gov. Landsat 7 satellite program. These techniques uses a Convolutional Neural Network which is pretrained on one of the dataset and then train the network to predict the nightlight light intensity analogous to input daytime satellite imagery. In the end, a model is trained to directly estimate the local per capita outcomes from daytime image features [9]. The features learned in one model can be used for some other model. To predict the location of the center of the place as well as latitude and longitude, a Google Geocoding API is used. Multi-task learning involves learning multiple tasks exclusively while determining the similarities and differences among the tasks [8] [1]. The suitable input to a model is a 1920*1920 sized image of a region. Nightlights serve as a good proxy for predicting the wealth. Raw satellite images is used for extracting the socioeconomic indicator [8]. The transfer learning approach not only predict the nightlight intensity but also helps in mapping poverty. The goal of transfer learning is to transfer the knowledge to the target problem of predicting nighttime light intensity from daytime satellite imagery. Per capita consumption cannot be estimated as nightlights have difficulty in distinguishing between poor, densely populated, and wealthy and sparsely populated areas [13]. Predicting the poverty can also be done by using the Multi-Task learning which involves learning different types of tasks simultaneously and also evaluating the similarities and differences between them. In Multi-Task Fully Convolutional Model, the Convolutional block comprises of Convolutional Layer, [8] A Batch Normalization Layer. The accuracy of the model is determined by the calculating the Pearson's Correlation Coefficient i.e. r^2. The relationship between the household data and remote sensed data differ at the community level [12]. The Wikipedia Model learn associations with poverty and outperforms nightlights only [14]. The Recurrent Network can be placed on the top of the Convolutional Neural Network so that prediction across years can be determined and poverty forecasting. The basic understanding developed by reviewing the survey is that these satellite images can be successfully used in order to predict the poverty index of the particular region. This approach gave better understanding in analyzing the poverty issues in several African countries.

III. PROPOSED APPROACH

Our idea is to predict the poverty index of a particular region in India. It is inspired by the successful use of deep learning approaches for poverty prediction in several African countries as appreciated in literature. With this paper, we want to estimate the correlation of poverty predicted from satellite images and wealthscore obtained from DHS survey data of India. On successful implementation, the result obtained will be compared with the result obtained from ground-level surveys. Firstly, the model takes Demographic and Health Survey Data i.e. Household Data (dataset has record for each individual) and Geographical Data (Health Data, Infrastructure such as roads, buildings linked with DHS Data). It further generates information of the cluster and Household Data containing the wealthscore, cluster wealth, latitude and longitude. This raw survey data is then used to produce more refined clusters. Then the extracted cluster data is processed to generate image coordinates. The image coordinates are generated in order to download the images of size 400 * 400 pixels using HERE Maps API which is later resized of size of 299 * 299 pixels. Similarly, the nightlight image is downloaded from the DMSP-OLS of size 43201 x 16801 pixels. The downloaded daylight images are then divided into 3 classes based on nightlight intensities of identical regions acquired from nightlight image. These 3 classes are Low [0-7 nightlight intensity], Medium [8-15 nightlight intensity] and High [16-63 nightlight intensity].

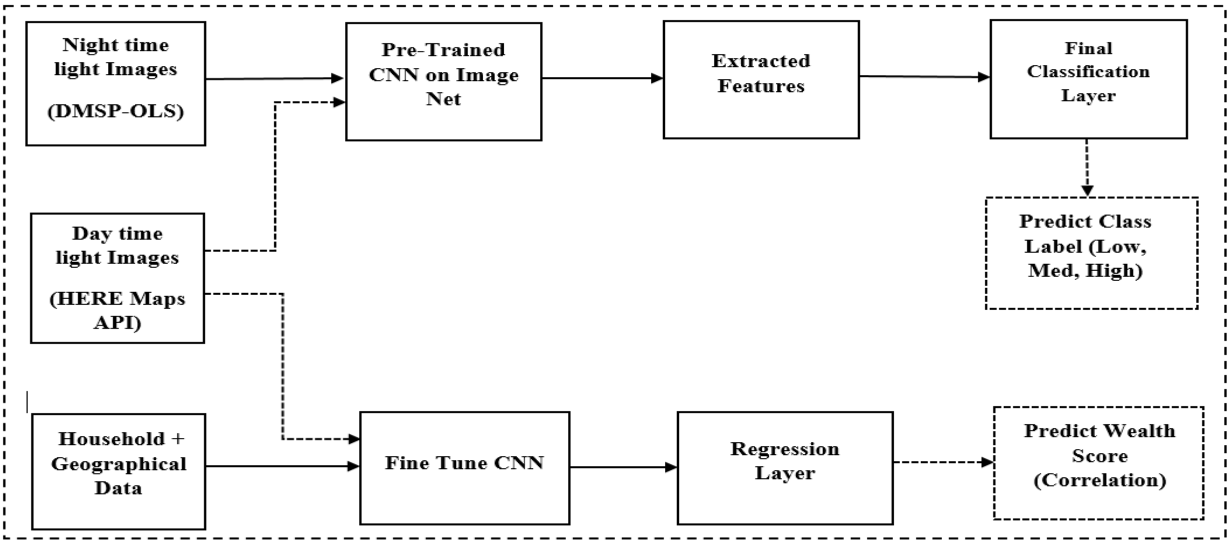

Fig.1: Proposed Framework using Inception V3

Used pre-trained model of Inception V3 is trained on ImageNet Database [16] with thousands of images. The network is covered with 48 layers and classified into 1000 image categories. The size of image in the network is 299 x 299 pixels. The Inception code uses TF-slim, which seems to be a kind of abstraction library over Tensor Flow [15]. As a result, model has learned rich feature representation for a wider range of images. The Parent Layers in the Model are Basic Conv2d and Inception A/ Batch Conv2d. The sub-layers include Conv-2d and Batch-Norm 2d. The Model includes Total Number of Parameters, Number of Trainable Parameter and Non-Trainable Parameter.

We used PyTorch library to build our Convolutional Neural Network model pretrained which is a pre-trained network of Inception V3. The daylight satellite images are taken as input to this pre-trained model to extract the features for further classification. Class labels obtained from nightlight regions of image are used in final classification layer for classification of daylight images. The DHS data is used in regression model for measuring correlation between predicted values from model and actual assets value.

Different trainable and non-trainable parameters used in our network are listed in Table 1. The configuration of architecture used for training of CNN model is demonstrated in Table 2.

Table 1: Different parameters of Trained Model Inception_V3

Total Parameters:	2,17,91,715
Trainable Parameters:	1,28,25,859
Non-trainable Parameters:	89,65,856

Table 2: Convolutional Neural Network Configuration Setup

Perimeter	**Value (Range)**
Classes	3

Batch Size	64
Number of Workers	4
Learning Rate	0-1
Momentum	0.9
Step Size	8
Gamma	0.1
Loss	Cross Entropy Loss
Image Size	299*299

Daylight satellite images are classified into 3 classes on the basis of the nightlight intensities obtained from night time light images obtained from DMSP-OLS. These 3 classes are low, medium and high. The training and test data is processed in the batch sizes of 64 on 4 workers. The learning rate and momentum is varied in the range of 0 to 1 and the best results attained are mentioned in Table 3. Cross entropy loss is analyzed for 60000 daylight images of size 299* 299.

IV. IMPLEMENTATION AND RESULTS :

Table 3: Accuracy & Loss analysis on different value of Learning Rate

Model		**Accuracy & Loss**				
		Batch Size=64, Epoch = 30				
Pre-Trained	**Momentum**	**Learning Rate**	**Train Accuracy**	**Train Loss**	**Test Accuracy**	**Test Loss**
TRUE	0.9	0.001	99.95	0.35	78.54	92.82
		0.0001	65.76	1.11	64.29	77.48
FALSE		0.001	55.11	1.28	58.72	87.12
		0.0001	49.5	1.38	50.53	96.33

i. For Trained Model (Pretrained = True)

As shown below in Fig. 2, the training loss decline from 1st to 5th iteration and drops from the 5th iteration because rate of learning is gradually depressed by 10. The test loss initially depressed till 2nd iteration but starts incrementing after 3rd iteration and remain constant throughout. Alike, the training accuracy grows from 1st to 5th iteration and then concur slowly to a soaked state due to gradually degraded rate of learning. The test accuracy increases at a great rate till 4th iteration and then comes to a saturation state.

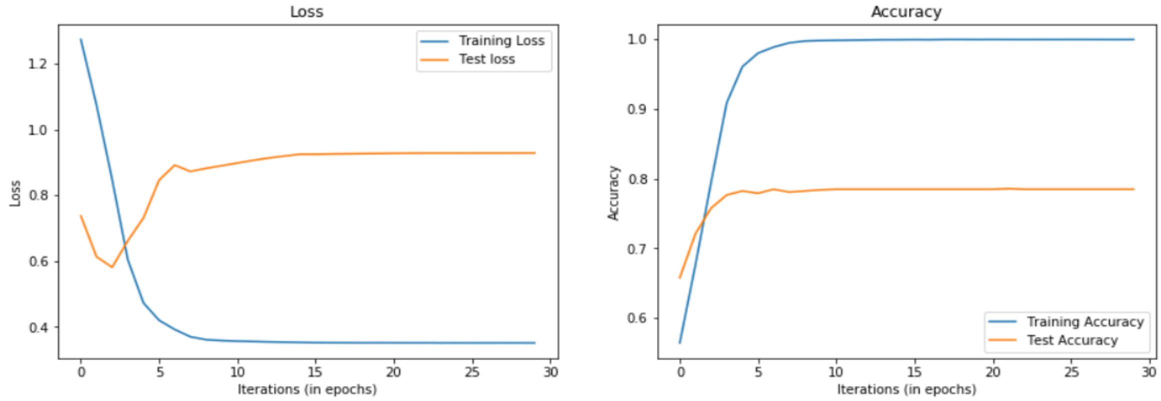

Fig. 2: Loss & Accuracy Graph Vs. Iteration on Nightlight Intensities with Learning Rate = 0.001 and Pretrain Model= True

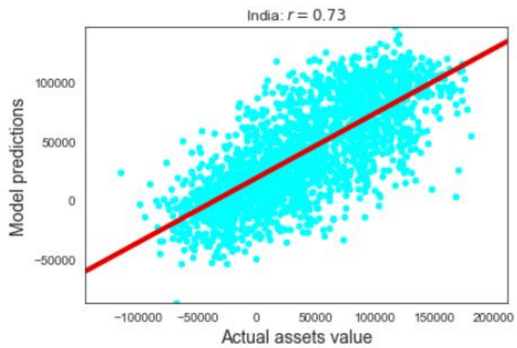


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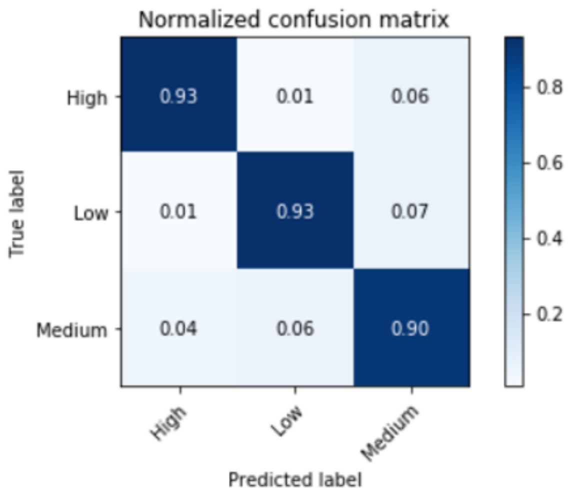
Fig. 3: Comparison between wealthscore between actual assets value and model predictions

The results as shown in Fig. 3, depicts that predictions of our model are accurately defined with r value of 0.73.



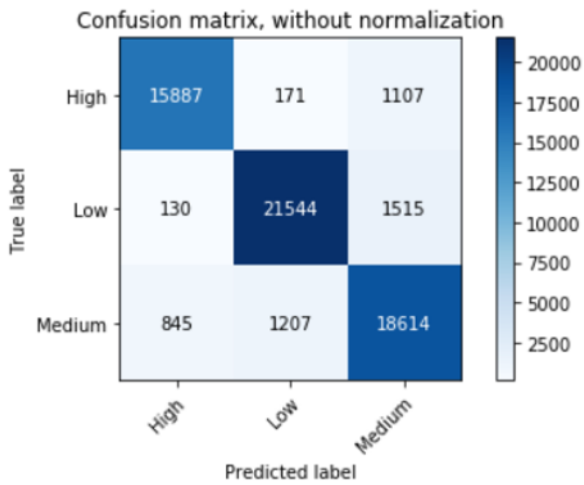


Fig. 4(a): Confusion Matrices' with Normalization

Fig. 4(b): Confusion Matrices' without Normalization

Confusion Matrices for High, Medium and Low classes Normalization and against Normalization are shown in Fig. 4(a) and 4(b).

ii. **For Trained Model (Pre-trained = False)**

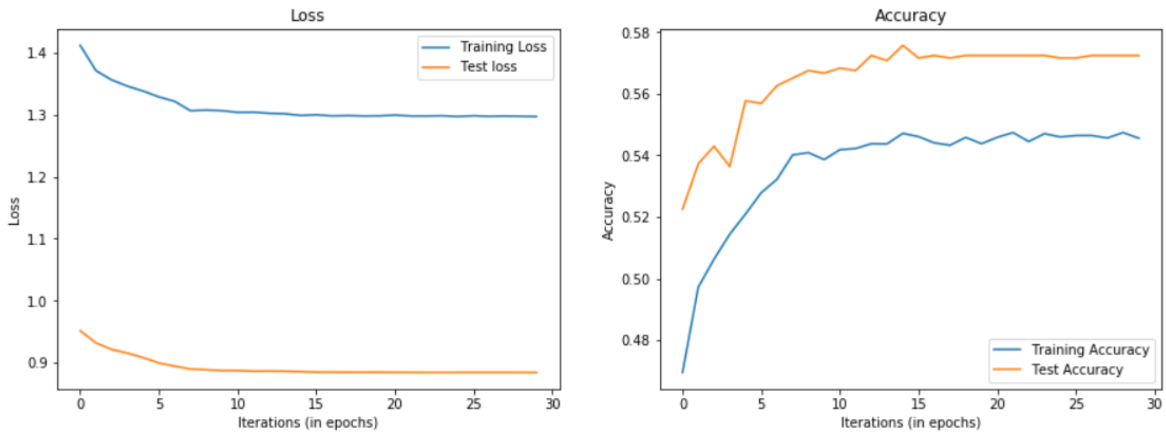


Fig.5: Loss & Accuracy Graph Vs. Iteration on Nightlight Intensities with Learning Rate = 0.001 and Pretrain Model=False

As shown in Fig.5, the training loss decreases steadily up to 7th iteration, and then remain constant till the last due to constant value of learning rate. The test loss in the starting remains very less and keeps decreasing slowly till the 7th iteration then remain constant for the rest of the epochs. Similarly, the training accuracy in the starting increases rapidly from 1st to 6th iteration but shows frequent deflection throughout the end due to degraded rate of learning. The test accuracy on the other hand, shows the deflection in the value from the 1st iteration and after the 15th iteration the value remains constant.

The results below in Fig. 6, depicts prediction of model with pretrain (false) gave r value of 0.74 accurately considering the issues that Household DHS data preserve the invisibility of the survey and CNN can also be trained optimally in the future.

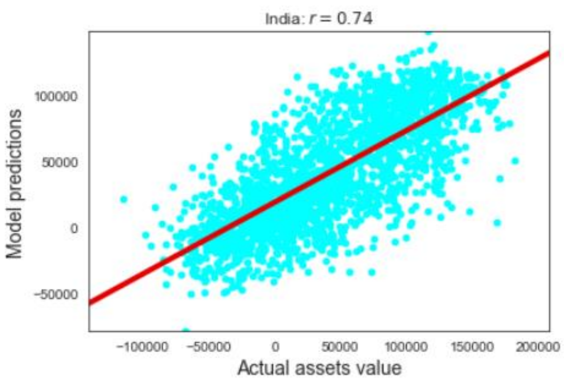



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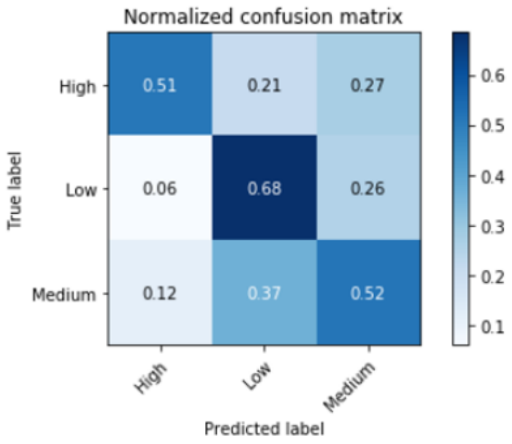
Fig.6: Comparison between wealthscore of true and predicted cluster

Confusion Matrices for classes with and without Normalization are shown in Fig. 7(a) and 7(b).



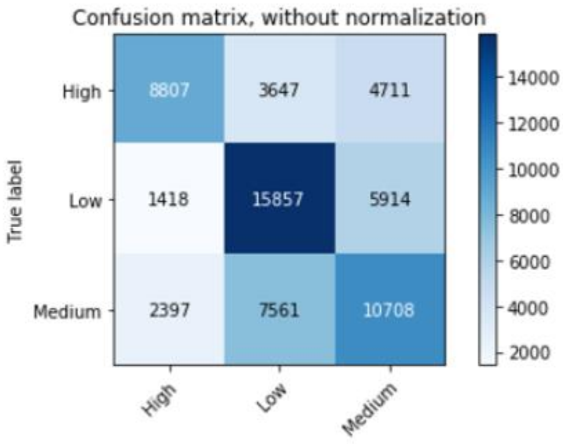


Fig. 7(a): Confusion Matrices' with Normalization **Fig. 7(b):** Confusion Matrices' without Normalization

V. CONCLUSION

We discussed in literature that how machine learning techniques can be used to predict the socio-economic parameter (poverty index) using remote sensing and household survey data. It motivated us to identify the scope of using pre-trained model for assessing poverty levels of regions. We also explored and analysed the results to establish the strong correlation between wealth score obtained from DHS and poverty levels obtained from daylight and nightlight satellite imagery. The daylight satellite imagery were downloaded from the HERE Maps API and analysed these images on pre-trained convolutional neural network Inception_V3. The fine tuning of the pretrained model improved extraction of features from daylight and nightlight images in comparison to a basic model (pre-trained=False) with reduced computation time. The Ridge regression model is used further to measure the r value (Pearson Correlation Coefficient) which is 0.73. It will surely reduce human efforts and cost of collecting data manually and ensure the authenticity of the correct prediction of wealth score of any particular region. Facts that can be considered for future enhancements are –

- It can be used by government in order to build different and effective policy to predict the poverty in different regions.
- Different pre-trained CNN models and also Recurrent Neural Networks can be used for better results.
- Use of Google Static Maps instead of HERE Maps API which may provide other kind of information also to accommodate in the prediction for more accurate results.
- The idea is also inspired with the state of being able to see evolution of Digital India.

REFERENCES

[1]. Jean, Neal, Marshall Burke, Michael Xie, W. Matthew Davis, David B. Lobell, and Stefano Ermon. "Combining satellite imagery and machine learning to predict poverty." Science 353, no. 6301 (2016): 790-794.

[2]. Russakovsky, Olga, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang et al. "Imagenet large scale visual recognition challenge." International journal of computer vision 115, no. 3 (2015): 211-252.

[3]. Daylight Images, Google HERE Maps API, www.here.com

[4]. Nightlight Images, DMSP-OLS Dataset, https://ngdc.noaa.gov/eog/dmsp/
[5]. DHS program, https://dhsprogram.com/data/available-datasets.cfm
[6]. United Nations, “A World That Counts: Mobilising the Data Revolution for Sustainable Development” (2014).
[7]. Sustainable Development, United Nations. Sustainable Development Goals: 17 Goals to Transform Our World. Available at: http://www.un.org/sustainabledevelopment/ sustainable-development-goals/
[8]. Pandey, Shailesh M., Tushar Agarwal, and Narayanan C. Krishnan. "Multi-task deep learning for predicting poverty from satellite images." In Thirty-Second AAAI Conference on Artificial Intelligence. 2018.
[9]. Rastogi, Ruchir. "Temporal Poverty Prediction In Developing Countries".
[10]. Living Standard Measurement Survey, The World Bank, www.worldbank.org/lsms
[11]. Blumenstock, Joshua Evan. "Fighting poverty with data." *Science* 353, no. 6301 (2016): 753-754.
[12]. Watmough, Gary R., Charlotte LJ Marcinko, Clare Sullivan, Kevin Tschirhart, Patrick K. Mutuo, Cheryl A. Palm, and Jens-Christian Svenning. "Socioecologically informed use of remote sensing data to predict rural household poverty." Proceedings of the National Academy of Sciences 116, no. 4 (2019): 1213-1218.
[13]. Xie, Michael, Neal Jean, Marshall Burke, David Lobell, and Stefano Ermon. "Transfer learning from deep features for remote sensing and poverty mapping." In Thirtieth AAAI Conference on Artificial Intelligence. 2016.
[14]. Sheehan, Evan, Chenlin Meng, Matthew Tan, Burak Uzkent, Neal Jean, Marshall Burke, David Lobell, and Stefano Ermon. "Predicting economic development using geolocated wikipedia articles." In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 2698-2706. 2019.
[15]. Abadi, Martín, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado et al. "Tensorflow: Large-scale machine learning on heterogeneous distributed systems." arXiv preprint arXiv:1603.04467 (2016).
[16]. ImageNet, Database, http://www.image-net.org
[17]. Sustainable Development Goals, https://sustainabledevelopment.un.org
[18]. Poverty, Economics, https://www.investopedia.com/terms/p/poverty.asp
[19]. Satellite Images, Prediction Economic Indicator, https://economictime Indiatimes.com/news/economy/policy/satellite-images-data-to-help-predict-economic-indicators
[20]. Agarwal Parth, Garg Nandishwar, Singh Pratibha. “Predicting Poverty index using Deep Learning on remote sensing and household data”, IJRTE, 2019, 164-168.
[21].abs/1603.04467, 20 1 Abadi, Martín, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado et al. "Tensorflow: Large-scale machine learning on heterogeneous distributed systems." arXiv preprint arXiv:1603.04467 (2016).
[22].Martin Abadi, Ashish Agarwal, et aI, TensorFlow: Large-ScaleMachine Learning on Heterogeneous Distributed Systems. CoRR
[23].abs/1603.04467, 20 16.
[24].Martin Abadi, Ashish Agarwal, et aI, TensorFlow: Large-ScaleMachine Learning on Heterogeneous Distributed Systems. CoRR
[25].abs/1603.04467, 20 1