PREDICTING POVERTY LEVEL USING SATELLITE IMAGERY

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Abstract - This paper provides an idea for predicting the poverty level. The project comprises of detecting the poverty level by using a satellite imagery Using a recurrent neural network. The dataset is in image format that is satellite image of a region. Several libraries also used such as matplotlib etc. divided the initial images into training, tuning, and testing sets. The splits were executed on the country level to ensure that data from the same country is not in more than one set. Furthermore, the splits were consistent across daytime and nighttime images meaning that daytime and nighttime images of the same region were in the same split, ensuring consistency in reporting metrics across daytime and nighttime experiments All evaluation is done on held-out test regions that were not used in model development. This mimics the real world usage of such a network, where the network is expected to make predictions on regions unseen during training. After that clustering will happen based on the number we gave and then predicting process will be done it will tell the wealth of the region. In this research paper, different Satellite images has been collected and machine learning algorithm is used.

Keywords: Machine learning, Poverty level prediction, Poverty Level, Clusters, Satellite Images, Recurrent neural network.

I. INTRODUCTION

A nation's citizens should be aware of their own economic situation. Knowing the statistics on poverty is crucial for social analysts who need to determine the state of the local economy. In this study, we only use satellite pictures to determine a region's poverty level. This information on poverty levels will help the government decide whether to improve the area's standard of living, or poverty level, or not. We used satellite pictures and databases with various data points to determine the poverty level. Using a "Recurrent Neural Network" deep learning algorithm, the machine will be trained to determine the value for every location in the world.The project comprises of detecting the poverty level by using a satellite imagery Using a recurrent neural network. The dataset is in image format that is satellite image of a region. Several libraries also used such as matplotlib etc. divided the initial images into training, tuning, and testing sets. The splits were executed on the country level to ensure that data from the same country is not in more than one set. Furthermore, the splits were consistent across daytime and night time images meaning that daytime and night time images of the same region were in the same split, ensuring consistency in reporting metrics across daytime and night time experiments All evaluation is done on held-out test regions that were not used in model development. This mimics the real-world usage of such a network, where the network is expected to make predictions on regions unseen during training.

Between 9.1% and 9.4% of the world's population is estimated to be on less than $1.90 a day this year. These projections are very similar to the 9.2% worldwide poverty rate for 2017, which indicates a three-year setback for the objectives of reducing poverty. In this blog, we extend our projection of poverty until 2030.






Using satellite pictures and remote sensing techniques, this research aims to develop a model that can forecast the levels of poverty in a given area. Convolutional neural networks specifically have showed potential in forecasting the intensity of nighttime lights, which can then be used to determine the underlying level of poverty. This will benefit philanthropic organizations and the government in determining where resources and initiatives are required, helping to steer the flow of money and other forms of assistance. Agencies are better able to monitor progress towards the Sustainable Development Goals when they have regular access to accurate data on the distribution and levels of poverty.

II. RELATED WORK

The paper titled "Satellite-Based Mapping of Urban Poverty with Transfer-Learned Slum Morphologies" When it comes to slums, satellite-based mapping helps fill in the gaps of knowledge on their location and size. Fuzzy feature spaces between formal and informal settlements, a high imbalance of slum occurrences relative to formal settlements, and many types of multiple morphological slum traits all make large-scale slum mapping difficult. With the help of high-resolution satellite data, we suggest a transfer learnt fully convolutional Xception network (XFCN) that can distinguish between formal built-up structures and the various types of slums.

A) The paper titled "Using Convolutional Neural Networks on Satellite Images to Predict Poverty as the poorest continent, Africa is the subject of this essay. Three datasets containing satellite photos for three African nations with varying levels of poverty—Ethiopia, Malawi, and Nigeria—make up the data we've used. In addition to our unique CNN structure, two pre-trained Convolutional Neural Networks models (ResNet50 and VGG16) were used to identify the satellite photos.

B) The paper titled "Poverty Level Prediction Based on E-Commerce Data Using K-Nearest Neighbor and Information-Theoretical-Based Feature Selection." Several techniques might be employed in this extremely quick development to calculate the level of poverty. One of them is by using the E-commerce industry's rapid growth in Indonesia to gauge the country's level of poverty. In this paper, K-Nearest Neighbor and Information Theory Based Feature Selection were used to suggest a strategy for predicting the poverty level based on an e-commerce dataset.

C) The paper titled " Predicting Poverty through Machine Learning and Satellite Images" In this study, I create a machine learning model that uses deep learning, transfer learning, and the random forest algorithm to forecast the amount of poverty in three African nations based on satellite imagery. I used the VGG-11 network to extract features from satellite photos, and I then fed those data into the random forest model. Also, I utilised the perturbation-based technique occluded in the Septum package to investigate the CNN model's feature importance and locally linear embedding to visualise the distribution of features taken from various locations.

D) The paper titled "Poverty Prediction Through Machine Learning" The research takes into account that poverty is the result of multidimensional causes and proposes a number of useful machine learning models for such prediction, none of which fully account for the situation since some factors may outweigh others. In order to make predictions, it is therefore necessary to combine the information from the Oxford Poverty &

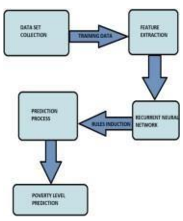
Human Development Initiative and the Poverty Probability Index. The paper evaluates the importance of the factors and the effectiveness of each model by applying the linear regression model, the decision tree, the random forest, the gradian boosting, and the neural network to the analysis of existing data.

III.RATIONALE FOR THE PRPOSED WORK AND RELATED WORK

More specifically, one may estimate poverty in some places using both day and nighttime satellite photography of those regions. Recent advances in a variety of computer vision tasks, including picture classification, segmentation, and object recognition, can be largely attributed to deep learning. We compile a dataset of 88,386 pictures from 44,193 cities in Africa, South America, Asia, Europe, and the Caribbean for this project. We collect a daylight satellite image, a nighttime satellite image, and the wealth index for each city. In order to forecast a city's wealth index given a satellite image, recurrent neural networks (RNNs) must first be trained.

System Architecture

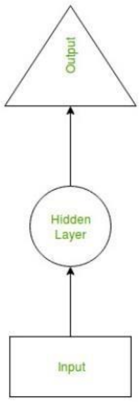
Unquestionably, one of the most fascinating divisions of artificial intelligence is machine learning. It successfully completes the goal of teaching the machine from data with specific inputs. Understanding how machine learning operates and, consequently, how it might be applied in the future, is crucial. The first step in the machine learning process is feeding the chosen algorithm with training data. The final machine learning algorithm is developed using training data, which might be known or unknown data.



The method is affected by the type of training data input, and that idea will be discussed in more detail shortly. The machine learning algorithm is fed fresh input data to see if it functions properly. The prediction and outcomes are then compared to one another. The algorithm is repeatedly retrained if the prediction and results don't line up until the data scientist achieves the desired result. As a result, the machine learning algorithm can continuously train on its own and produce the best solution, steadily improving in accuracy.

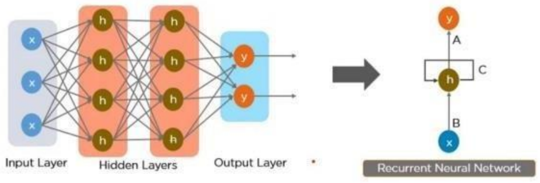
Recurrent Neural Network

Recurrent neural networks (RNNs) are a kind of neural networks in which the results of one step are fed into the current step's input. Traditional neural networks have inputs and outputs that are independent of one another, but there is a need to remember the previous words in situations where it is necessary to anticipate the next word in a sentence. As a result, RNN was developed, which utilised a Hidden Layer to resolve this problem. The Hidden state, which retains some information about a sequence, is the primary and most significant characteristic of RNNs.



Recurrent neural network benefits: Over time, an RNN remembers every single bit of information. Just the ability to remember past inputs makes it helpful for time series prediction. Long Short-Term Memory is the term for this. To increase the effective pixel neighborhood, convolutional layers and recurrent neural networks are combined. Recurrent neural network drawbacks: Problems with gradient vanishing and exploding.t is exceedingly tough to train an RNN.

If employing tanh or relying on an activation function, it is unable to parse very long sequences.



HOME PAGE: After running the project code in anaconda prompt ,a URL link will be displayed in the terminal .We have to copy that and paste it in any browsing website. At that time the project website will be opened. The home page contains the full details of the project and having the login button by which we can get into the project with appropriate password. LOGIN PAGE: The login page contains the username and password input boxes in which we have to give the appropriate data to open into the next page. CLUSTERING PAGE: In this page, we have to give a image input to cluster the places based on some criteria and map them with different colors. This page will give a good visualization for the people for better understanding about the region.

PREDICTION PAGE: This will be the main core page, In which we have to give a image as input and the machine will predict the wealth of that area using recurrent neural network. And give a wealth value at the bottom of the page. ANALYSIS PART: In this page, the project analysis i.e., the accuracy map and some analysis taken part .

Recurrent Neural Networks, often known as RNNs, are a crucial subset of neural networks that are frequently employed in natural language processing. They belong to a type of neural networks that, while maintaining hidden states, permit the use of prior outputs as inputs. The "memory" notion used by RNNs stores all data related to calculations made up to time step t. Recurrent neural networks (RNNs) are so named because they consistently complete the same task for every element in a sequence, with the results depending on earlier calculations. Let’s first examine why RNNs are used before delving deeply into what a recurrent neural network is and how it works. An input is fed into an input layer of a general neural network, which then processes the input through a number of hidden layers to produce the final output under the assumption that two successive inputs are independent of one another or that the input at time step t has no relation to the input at time step. Unfortunately, there are some situations in actual life where this presumption is false. Dependence on prior observations must be taken into account, for example, if one wants to forecast the price of a stock at a specific moment or the subsequent word in a series.

IV. CONCLUSION AND FUTURE ENHANCEMENT

The goal of this Project was to examine a novel approach to poverty prediction using both daytime and night-time satellite images. While there is more to do, we think our work can provide a basis for poverty prediction as well as show its potential. Identifying regions of poverty is the first step on its reduction and believe this work has contributed.

In future along with poverty level it will tell what wealth has to improve to get rid of poverty.

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