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Predicting Poverty Level From Satellite Imagery Using Ensemble Learning

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A B S T R A C T

In order to effectively reduce poverty, it is essential to measure and follow support initiatives over time in order to focus aid efforts and inform policy choices. However, gathering such data requires a lot of time and effort, thus coverage of places plagued by poverty is frequently scant or nonexistent. Previous studies have demonstrated the viability of using remote sensing techniques to measure poverty levels. Particularly, convolutional neural network processing of satellite pictures has demonstrated potential in forecasting the intensity of nocturnal lights, which may then be used to determine the underlying poverty level. By figuring out ways to gauge changes in poverty levels over time using the same kind of readily accessible data, this initiative aims to build on earlier research. We are able to confirm the initial findings of the single-point poverty prediction. To meaningfully anticipate temporal poverty, further work is still required. In order to find interventions for projects to reduce poverty and equitably allocate resources, it is essential to ascertain the levels of poverty in different regions of the world. However, it is difficult to find accurate information on global economic conditions, particularly for regions in the developing world. This hinders efforts to both implement services and monitor/evaluate success. The goal of this research is to use satellite imagery to identify economic activity and, as a result, gauge the level of poverty in a certain area. A recurrent neural network is trained to understand several development characteristics, such as the type of rooftop, the illumination source, the distance from water sources, agricultural areas, and industrial areas.

Keywords : Economic Conditions, Poverty, Water Sources

I. INTRODUCTION

1.1 What is Machine Learning?

A system of computer algorithms known as "machine learning" is capable of learning from experience and improving itself without having explicit programming. Artificial intelligence includes machine learning, which uses statistical methods and data to predict an outcome that can be utilised to generate actionable insights. The innovation is based on the notion that a machine can create accurate results just by learning from the data (i.e., examples). Data mining and Bayesian predictive modelling are strongly related to machine learning. The computer takes data as input and generates answers using an algorithm. Making recommendations is a common machine learning problem. All Netflix recommendations for users who have an account are based on the user's prior viewing history. Unsupervised learning is being used by tech companies to enhance user experience with personalised recommendations. Another use of machine learning is to automate operations like fraud detection, predictive maintenance, portfolio optimisation, and so forth.

1.2 How is machine learning implemented?

The brain of machine learning is where all learning occurs. The way a machine learns is comparable to how a person learns. Experience is how people learn. The easier it is to forecast, the more we know. By analogy, our chances of success are lower than they would be in a known situation when we encounter one. Machines receive the same training. The computer observes an example in order to create a precise prediction. The machine is capable of predicting the result when we provide a comparable case. However, just like a human, the machine has trouble predicting if it is given a new example. Learning and inference are at the heart of machine learning. The first way the machine learns is by identifying patterns. The data allowed for this finding to be made. The data scientist's ability to carefully select the data to give the computer is one of their most important skills. A feature vector is a set of attributes that is used to solve an issue. A feature vector can be thought of as a subset of data that is utilised to solve a problem. The machine simplifies reality using some sophisticated algorithms, turning this discovery into a model. For instance, the machine is attempting to comprehend the connection between a person's pay and their likelihood of dining at a posh restaurant. It turns out that the computer detects a favourable correlation between income and dining at a fine restaurant: Here is the example.

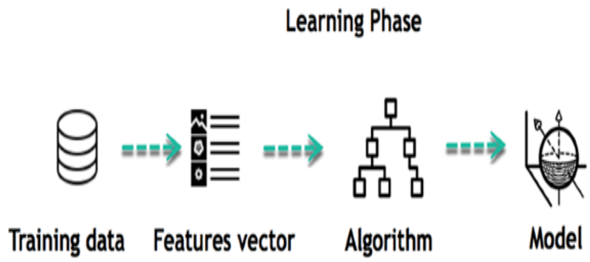

Figure 1.1 Working of ML

1.3 Supervised learning

An algorithm learns the link between given inputs and a particular output using training data and feedback from humans. For instance, a practitioner can forecast can sales using input data such as marketing expenses and weather predictions.

When the output data is known, supervised learning is an option. New data will be predicted by the programme.

Two types of supervised learning exist:

• Classification and regression exercises

1.4 Classification

Imagine you need to determine a customer's gender for a commercial. You'll begin pulling information from your customer database about their height, weight, occupation, salary, basket of purchases, etc. You are aware of each customer's gender, which can only be either male or female. Assigning a likelihood of being male or female (i.e., the label) based on the data (i.e., the attributes you have gathered) is the classifier's goal. You can use fresh data to predict once the model learned to distinguish between male and female.

1.5 Regression

The task is a regression when the output is a continuous value. For instance, a financial analyst can be required to predict the value of a stock based on a variety of factors, such as equity, past stock performance, and macroeconomics index. The system will undergo training to calculate stock prices with the least amount of error.

1.6 Artificial intelligence

AI's branch of machine learning. AI as a subfield of Machine Learning, or AI as a subfield of Machine Learning Machine learning is a field of study that developed from the search for artificial intelligence. Some academics were intrigued by the idea of letting computers learn from data in the early stages of AI as an academic field. They made an effort to approach the issue using a variety of symbolic techniques as well as what were at the time referred to as "neural networks"; these were mostly perceptrons and other models that were subsequently discovered to be reimaginings of the generalised linear models of statistics. Additionally, probabilistic reasoning was used, particularly for automated medical diagnosis.

1.7 Data mining

While machine learning concentrates on making predictions based on known properties learned from the training data, data mining concentrates on finding (previously unknown) properties in the data (this is the analysis step of knowledge discovery in databases). Machine learning and data mining frequently use the same methods and have a lot in common. In contrast, machine learning also uses data mining techniques as "unsupervised learning" or as a preprocessing step to increase learner accuracy. Data mining employs a variety of machine learning techniques, albeit with distinct purposes. Much of the misunderstanding between these two research communities—which frequently have separate conferences and journals, with ECML PKDD being a notable exception—results from the fundamental presumptions they operate under. For example, performance in machine learning is typically measured in terms of its capacity to replicate existing knowledge, whereas in knowledge discovery and data mining (KDD), the main objective is the discovery of previously undiscovered knowledge.

1.8 Artificial Nueral Networks

Similar to the extensive network of neurons in the brain, an artificial neural network is made up of interconnected groups of nodes. Each circular node in this diagram represents an artificial neuron, and each arrow shows how one artificial neuron's output connects to another's input. Computer systems called artificial neural networks (ANNs), also known as connectionist systems, are loosely modelled after the organic neural networks that make up animal brains. Such systems "learn" to execute tasks by taking into account examples, typically without having any task-specific rules written into them. A model known as an ANN is based on a set of interconnected "artificial neurons" that are meant to approximate the neurons in a biological brain. A "signal" can be sent from one artificial neuron to another through each link, just like synapses in a human brain. After processing a signal, an artificial neuron can signal other artificial neurons that are connected to it.

1.9 Decision trees

To move from observations about an item (shown in the branches) to inferences about the item's target value (expressed in the leaves), decision tree learning employs a decision tree as a predictive model. It is a technique for predictive modelling that is used in data mining, statistics, and machine learning. Classification trees are tree models where the target variable can take a discrete range of values. In these tree structures, the leaves correspond to class labels and the branches to the attributes that combine to form those class labels.

II. SYSTEM ANALYSIS

2.1 Existing system

- Currently, a variety of charitable organisations, including the World Bank, formally quantify poverty.
- Because on-the-ground surveys are expensive, there are a number of factors contributing to the lack of statistics on poverty in the developing world.
- The nation only becomes aware of where it stands in terms of income levels after this step.

2.2 Disadvantages of existing system

- The present issue in this field is the length of time it takes for agencies all around the world to anticipate income levels.
- Once completed, this subject is not brought up again until the subsequent decennial census.
- These kinds of undertakings not only need a significant amount of time, but also startling sums of money.For organisations and governments all across the world, this is a major headache.

2.3 Proposed system

More specifically, daylight and nighttime satellite images of regions can be utilised to estimate poverty in some places. Recent developments in deep learning give an interesting prospect for application to poverty prediction.

- Recent advances in a variety of computer vision tasks, including picture classification, segmentation, and object recognition, are largely due to deep learning.In this study, we investigate the claim that deep learning can effectively use satellite data to forecast a region's level of poverty.
- We compile a dataset of 88,386 photos from 44,193 cities in the Caribbean, Africa, South America, Asia, and Europe.
- We get a daylight and nighttime satellite image as well as the city's wealth index for each city.
- Afterwards, I train recurrent neural networks (RNNs) to forecast a city's wealth index using a satellite image.

III. IMPLEMENTATION

MODULES

- ❖ Data Collection
- ❖ Dataset
- ❖ Data Preparation
- ❖ Model Selection
- ❖ Analyze and Prediction
- ❖ Accuracy on test set
- ❖ Saving the Trained Model

3.1 Data Collection

This marks the beginning of the actual process of building a machine learning model and gathering data. This is a crucial phase since how well the model performs will be influenced by how much more and better data we can collect. Data collection methods include web scraping, manual interventions, and others. Comparison of Machine Learning Methods for Poverty Prediction obtained from kaggle and another source, hotspots.

3.2 Dataset

There are 821 distinct data points in the dataset. The dataset contains 27 columns, each of which is detailed below.

STATE: An Indian state

DISTRICT: A district in the Indian state.

Year: 2001-2018

Overall Poverty Total amount of poverty rate

3.3 Data Preparation

We'll change the data. by eliminating any missing data and some columns. The column names that we want to keep or retain will first be listed. After that, we drop or eliminate all columns save for the ones we wish to keep. Finally, we eliminate or remove the rows from the data collection that contain missing values.

3.4 Model Selection

Two datasets are required when building a machine learning model: one for training and the other for testing. But there is only one left now. Let's divide this in two according to an 80:20 ratio. The dataframe will also be split into a feature column and a label column. We imported the sklearn train_test_split function here. Use it to divide the dataset after that. Additionally, test_size = 0.2 divides the dataset into two parts: 20% for the test and 80% for the train.

3.5 Analyze and Prediction

We only selected 3 features from the actual dataset:
STATE: An Indian state
DISTRICT: A district in the Indian state.
Year: 2001-2018
Precision on the test set:
On the test set, we achieved accuracy of 95.1%, 97.1%, 98.1%, and 96.5%.

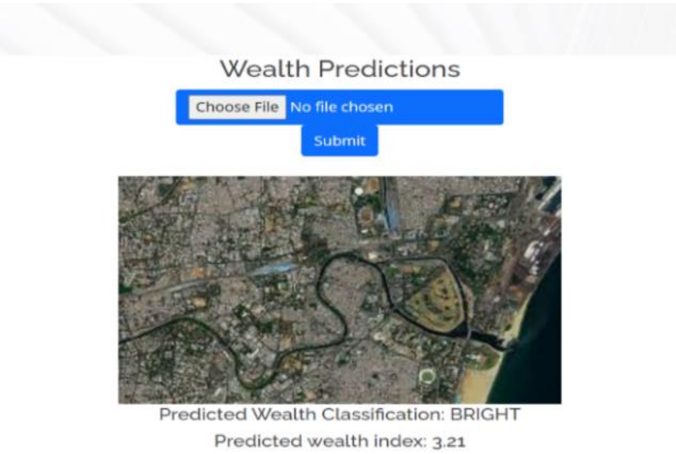

Figure 3.5 Software output

3.6 Saving the trained model

The first thing to do is store your trained and tested model into a.h5 or.pkl file using a library like pickle once you're ready to use it in a production-ready setting. Verify that Pickle is set up in your environment. The model will now be imported into the module and dumped as a.pkl file.

IV. SYSTEM REQUIREMENTS

4.1 Hardware Requirements

- System : Pentium IV 2.4 GHz.
- Hard Disk : 40 GB.
- Floppy Drive : 1.44 Mb.
- Monitor : 15 VGA Colour.
- Mouse : Logitech.
- Ram : 512 Mb.

4.2 Software Requirements

- Operating system : Windows .
- Coding Language : Python
- Database : MYSQL

V. CONCLUSION

- This project's objective was to investigate a novel method of predicting poverty using both daytime and nighttime satellite photos.
- Although there is more work to be done, we believe that our research can serve as a foundation and demonstrate the promise of poverty prediction.
- The first step in reducing poverty is to identify its hotspots, and I think my work has helped with that.

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