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Deep learning Based Water Conservation Geospatially

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Abstract
In this paper we discuss about the water which we face problem in more rainfall like flood and in dry we face water shortage. To overcome this we use Geospatial Technology which sends the water detail in the world and how we can save and wastage will be reduced. Some effect due to water can be overcome by this will be calculated by deep learning technique algorithms. Also some software like arcgis learn module in ArcGIS API for Python enables GIS analysts and data scientists to train deep learning models with a simple, intuitive API. ArcGIS Notebooks provides a ready-to-use environment for training deep learning models.

I. INTRODUCTION

Nowadays, people are physically isolated, but digitally connected due to advances in communication and information technology, and development of social media applications. Moreover, GIS applications development in web/internet enables users to collect, share and visualize geospatial data in a timely and cost-effective (built once, used many) manner. A few geospatial dashboards have been developed around the world.

Geospatial Technology is an emerging field of study that includes Geographic Information System (GIS), Remote Sensing (RS) and Global Positioning System (GPS). Geospatial technology enables us to acquire data that is referenced to the earth and use it for analysis, modeling, simulations and visualization. Geospatial technology allows us to make informed decisions based on the importance and priority of resources most of which are limited in nature. Geospatial technology may be used to create intelligent maps and models that may be interactively queried to get the desired results in a STEM application or may be used to advocate social investigations and policy based research. It may be used to reveal spatial patterns that are embedded in large volumes of data that may not be accessed collectively or mapped otherwise. Geospatial technology has become an essential part of everyday life. It's used to track everything from personal fitness to transportation to changes on the surface of the earth.

Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised from data that is unstructured or unlabeled. Also known as deep neural learning or deep neural network.

Geospatial data sharing

City Geospatial Dashboard, Data Sharing Module plays important roles in the disaster response stage. Proper information needs to reach disaster area at proper time from various groups. We designed the City Geospatial Dashboard as a data-sharing platform for researchers, practitioners, planners, and disaster response teams to speed up their works. For example, researchers are able to use other researchers' output as input data for building their research models to avoid duplicate data collection and processing tasks. Disaster response teams enable to search available dataset for current disaster area from anywhere in timely manners.

Geovisualisation and spatial analysis

Geovisualisation is a set of tools and techniques for analysing geospatial data and visualising the results interactively. Web-based geovisualisation is the ideal platform for disaster management, based on the built onceused many concept. In this City Geospatial Dashboard, we provide Near Realtime JAXA Rainfall Profiler and GIS ready dataset based on MW-IR (microwave infrared) algorithm integrating multiple earth resource satellites developed by (Global Satellite Mapping of Precipitation) project team in 2005. City Geospatial Dashboard, JAXA Global Rainfall Profiler provides near up-to-date rainfall information, and users can generate rainfall profiles with statistical values minimum, maximum and average for a specific region or watershed or other user-defined boundaries. Understanding spatial distribution patterns of population distribution and human mobility information is important in disaster management. Nowadays, human mobility information can be acquired from mobile phone and internet usages, crowdsourcing activities, and sensor network-based big data collection systems known as event data warehousing. Big data analytics is important to extract meaningful information from big data, such as discovering hidden spatial distribution patterns, space-time relationships, movement, and so on. In this City Geospatial Dashboard, we provide hourly grid population estimated from mobile CDR. In this research, we utilise mobile CDR to estimate a vector format fine-scale (100m) multi-temporal grid square population at one-hour intervals. To scale the mobile CDR users up to the actual population size, we computed a home user-based magnification factor for individual unique subscriber IDs by scaling with the census population over a seven-day period. To improve the accuracy in terms of spatial analysis, we extracted a human settlement area from a Landsat 8 Operational Land Imager (OLI) satellite image, to create landcover-weighted 100 m square grids, which were used to disaggregate Voronoi-based aggregated CDR data. Gridbased multitemporal population data is useful in many GIS analyses and is a clear means by which to visualize the change in human mobility over space and time.

Existing System

Till now water wastage in heavy rainy season, house hold and industry wasting more water. Some of the techniques existing are:

- Protection of Water from Pollution
- Redistribution of Water
- Rational Use of Groundwater
- Population Control
- Renovation of Traditional Water Sources
- Use of Modern Irrigation Methods
- Increasing Forest Cover

Proposed System:

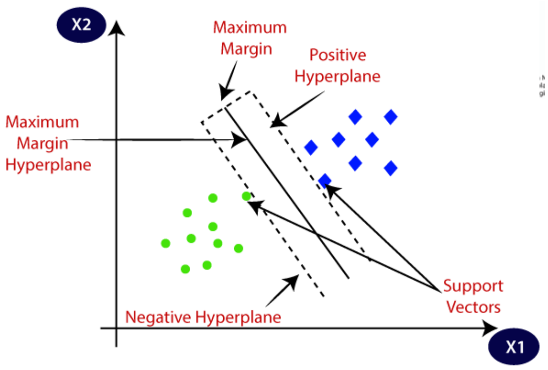
Geospatial and deep learning technique is used to classify the area where water is present. Water quality is monitored by water sensor. Remote sensing is used to sense the layer.

Vector Machine Algorithm

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

Here its used for water classification which chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:



SVM can be of two types:

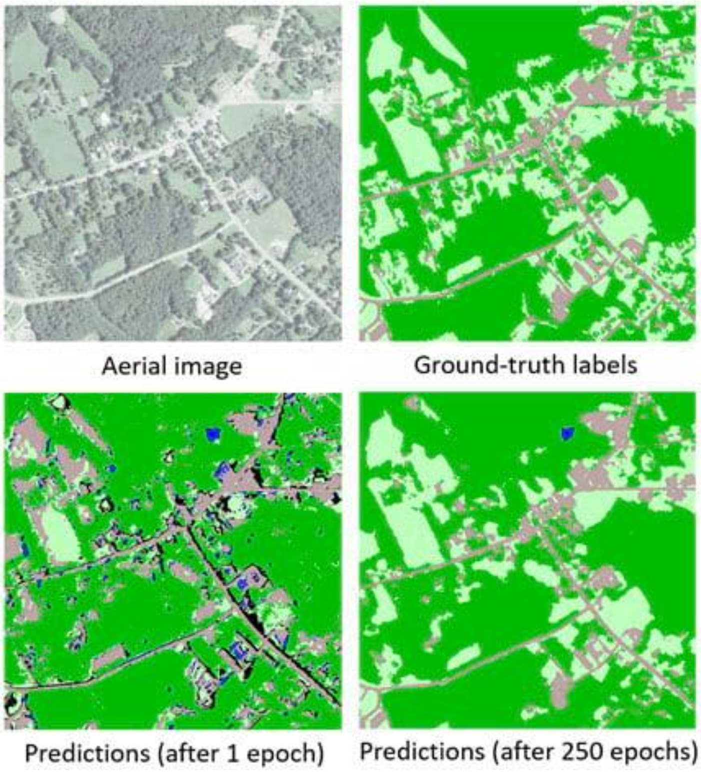
Linear SVM:

Linear SVM is used for linearly separable data, which means if a dataset can be classified into two classes by using a single straight line, then such data is termed as linearly separable data, and classifier is used called as Linear SVM classifier.

Non-linear SVM:

Non-Linear SVM is used for non-linearly separated data, which means if a dataset cannot be classified by using a straight line, then such data is termed as non-linear data and classifier used is called as Non-linear SVM classifier.

The support vector machine (SVM) is a predictive analysis data-classification algorithm that assigns new data elements to one of labeled categories. SVM has been successfully used in many applications such as image recognition, medical diagnosis, and text analytics.
ArcGIS is a platform for organizations to create, manage, share, and analyze spatial data. It consists of server components, mobile and desktop applications, and developer tools. ArcGIS Pro allows you to use statistical or machine learning classification methods to classify remote-sensing imagery. Deep learning is a type of machine learning that relies on multiple layers of nonlinear processing for feature identification and pattern recognition described in a model.
Clustering, which lets you process large quantities of input point data, identify the meaningful clusters within them, and separate them from the sparse noise. Prediction algorithms, such asgeographically weighted regression, give the ability to model spatially varying relationships. But it needs experts to identify or feed in those factors (or features) that affect the outcome that we're trying to predict.



Land-cover classification uses deep learning.

A nice early example of this work and its impact is the success the Chesapeake Conservancy has had in combining Esri GIS technology with the Microsoft Cognitive Toolkit (CNTK) AI tools and cloud solutions to produce the first high-resolution land-cover map of the Chesapeake watershed. This work is now also available as a tutorial and can be deployed on a Microsoft Data Science Virtual Machine (DSVM) on Azure.

Esri recently collaborated with NVIDIA to use deep learning to automate the manually intensive process of creating complex 3D building models from aerial lidar data for Miami-Dade County in Florida. See this detailed post "Reconstructing 3D Buildings from Aerial Lidar with AI: Details" on Medium or "Restoring 3D Buildings from Aerial Lidar with Help of AI" on the *ArcGIS Blog* to learn how this was done.

Integrating ArcGIS with AI

ArcGIS has tools to help with every step of the data science workflow including data preparation and exploratory data analysis; training the model; performing spatial analysis; and finally, disseminating results using web layers and maps and driving field activity. To add context and depth to your analysis, you can use content from Esri's ArcGIS Living Atlas of the World. This large collection of Esri-curated and partner-provided imagery can be critical to a deep learning workflow.

ArcGIS Pro includes tools for helping with data preparation for deep learning workflows and has been enhanced for deploying trained models for feature extraction or classification. ArcGIS Image Server in the ArcGIS Enterprise 10.7 release has similar capabilities, providing the ability to deploy deep learning models at scale by leveraging distributed computing. The arcgis.learn module in ArcGIS API for Python enables GIS analysts and data scientists to train deeplearning models with a simple, intuitive API. ArcGIS

Notebooks provides a ready-to-use environment for training deep learning models. ArcGIS includes built-in Python raster functions for object detection and classification workflows using CNTK, Keras, PyTorch, fast.ai, and TensorFlow. Additionally, we can write our own Python raster function that uses your deep learning library of choice or specific deep learning model/architecture. See this handy guide to get started.

Deep learning is a rapidly evolving field and allows data scientists to leverage cutting-edge research while taking advantage of an industrial-strength GIS. Python has emerged as the lingua franca of the deep learning world with popular libraries like TensorFlow, PyTorch, or CNTK chosen as the primary programming language. ArcGIS API for Python and ArcPy are a natural fit for integrating with these deep learning libraries, giving you more capabilities.

While the examples in this article have focused on imagery and computer vision, deep learning can be used equally well for processing large volumes of structured data such as observations from sensors, or attributes from a feature layer. Applications of such techniques to structured data include predicting the probability of accidents, sales forecasting, and natural language routing and geocoding.

II. CONCLUSION

In recent years, geospatial dashboards help many government agencies to monitor the water strength for sustainable development, effective urban and transport planning, public facility management, and disaster management. Moreover, City Geospatial Dashboard allows sharing the geospatial data between researchers to speed up their works. Advances in information and communication technology have changed the way we live, communicate, and acquire geospatial data by ever increasing of IoT devices. By constructing a Deep Learning model, we can find hidden spatial distribution patterns and spatio-temporal relationships. City Geospatial Dashboard plays important roles in collecting, sharing and visualising results to planners, decision-makers, and any geospatial information users in a timely manner.

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