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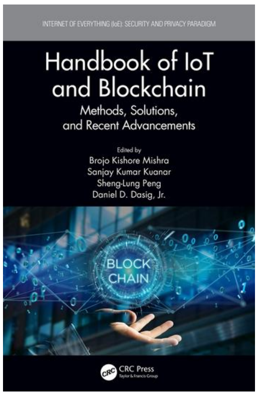


**Handbook of IoT and Blockchain**
**Methods, Solutions, and Recent Advancements**

Brojo Kishore Mishra, Sanjay Kumar Kuanar, Sheng-Lung Peng, Daniel D. Dasig

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# 10 Geospatial Data Classification using Sequential Pattern Mining with Modified Deep Learning Architecture

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## CONTENTS



## 10.1 INTRODUCTION

Advances in geographic information systems (GIS) provide an opportunity to gather, store, edit, query, verify, share and manifest geographically referenced information. In the case of earth science, a huge amount of data has been collected at various levels of granularity and this geospatial data is always big data [9][10]. At present, analysis of geospatial big data allows users to scrutinize huge amounts of geospatial data as this geospatial big data is spatial data sets that are beyond the capacity of current computing systems. For instance, the National Oceanic and Atmospheric Administration's (NOAA) satellites gather ocean, coast and atmospheric data of the global ecosystem for understanding and predicting changes in the Earth's environment [11]. The growth of this spatial data leads researchers to conduct further researches on spatial data mining techniques in a highly automated fashion.

Spatial data mining (SDM) is utilized for the extracting and mining of hidden, implicit, valid, novel and interesting spatial or non-spatial patterns or rules from

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large-amount, incomplete, noisy, fuzzy, random, and practical spatial databases [12] [13]. The efficiency of the SDM is based on the mining algorithm only. Moreover, one of the issues related to the SDM is that the geological data is typical spatial data, which includes geological, geophysical, geochemical, and remote sensing [14]. Big data is still not a clearly defined term and it has been defined differently from technological, industrial, research or academic perspectives. So, for solving these issues, the big data is classified as structured and unstructured datasets with massive data volumes that cannot be easily captured, stored, manipulated, analyzed, managed or presented by traditional hardware, software or database technologies since big data is often described by its unique characteristics [15].

Geospatial big data can be characterized by the following [22]: (a) Volume: Records sensed imagery data in Petabytes. Increase in data sets produces massive issues in storage (b) Variety: Includes the map data, imagery data, geo-tagged text data, structured and unstructured data, raster and vector data, (c) Velocity: imagery data with frequent revisits at high resolution, continuous streaming of sensor observations, Internet of Things (IoT), real-time GNSS trajectory and social media data all require matching the speed of data generation and the speed of data processing to meet demand (d) Veracity: much of geospatial big data is from unverified sources with low or unknown accuracy; the level of accuracy varies depending on data sources, raising issues about quality assessment of source data and how to "statistically" improve the quality of analysis results. (e) Visualization: This helps analysts identifying patterns (such as outliers and clusters), leading to new hypotheses as well as efficient ways to partition the data for further computational analysis. (f) Visibility: the emergence of cloud computing and cloud storage has now made it possible to efficiently access and process geospatial big data in ways that were not previously possible [16][17]. The variation in the format of data collection and increase in the volume of data are a challenging issue to geospatial data processing as it creates issues in storing, managing, processing, analyzing, visualizing and verifying the quality of data [18][21]. Moreover, the verification in the quality of geospatial big data and data products delivered to end-users is another challenging issue in quality control. On the other hand, fitness of uses or purposes appears more valid or should be advocated in the context of big data [19][20].

## 10.2 RELATED WORKS

In 2015, Hillen *et al.* [1] proposed the Geo-reCAPTCHA (Completely Automated Public Turing test to tell Computers and Humans Apart) in order to gather user-generated geographic information (UGCI) from earth observation data, as the UGCI was utilized for geography and geographic information science (GIScience). The Geo-reCAPTCHA approach was mainly based on assessing the time and quality of the resulting geographic information. Most of the problems related to the building digitization were solved within a short amount of time (19.2 s on average) and the accuracy of digitization in geospatial data was improved to 82.2%. Moreover, Geo-reCAPTCHA had high performance when compared to the reCAPTCHA. Thus, Geo-reCAPTCHA was a data-rich channel belonging to crowd-sourced geographic information.

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In 2015, Kebler *et al.* [2] proffered the time geography for the purpose of querying and integrating multiple spatial–temporal data sources and this framework was designed under the perception of the space–time prism and this was based on the constraints and interactions between entities in space and time. This research primarily developed the space–time prisms and then applied it to the Web of Data to get efficient spatial–temporal aspects. This research mainly focused on monitoring the environment with the space–time prisms and thus the spatial–temporal and semantic reasoning was obtained with the geospatial information and this information was gathered directly from distributed data sources.

In 2018, Xia *et al.* [3] accessed three earth observations (EO), namely fast access, accurate service estimation and global access with the help of accessing big data. Moreover, the research explored the spatial pattern, temporal pattern and spatio-temporal pattern of user-data interactions. With the help of these patterns, geospatial information was gathered by overcoming the drawbacks associated with the spatiotemporal patterns when end-users access EO data. This research also solved the problems associated with the utilization of spatiotemporal patterns for facilitating better EO big data access with the help of three spatiotemporal optimization strategies; they are (i) spatiotemporal indexing to accelerate data access, (ii) spatio-temporal service modeling to improve data access accuracy and (iii) spatiotemporal cloud computing to enhance global access. This research had a better framework in the optimization of EO big data access and was also vulnerable to other multidisciplinary geographic data and information research.

In 2018, Lu *et al.* [4] projected the GreenBDT: Renewable-aware scheduling of bulk data transfers for geo-distributed sustainable datacenters for the purpose of minimization of grid energy cost for bulk data transfers between sustainable and green datacenters and for maximizing the usage of renewable energy. GreenBDT was made possible with the heuristic algorithm in order to solve the MaxGreen-Min-Cost problem. This algorithm is employed with the following constraints; in case available wind power was not enough for the transfer all the bulk data, then the wind energy was utilized for the interGD BDTs or in case of insufficient wind power, then the inter-GD BDTs used optimal demand division and routing selection to minimize the energy cost caused by grid power. This research further revealed that validation with the real-life network topology optimized the scheduling for inter-datacenter bulk data transfers individually. This further suggested that the renewable energy was maximized. More securitized results proved that with real-life network topology, existing wind power and electricity prices, with maximum renewable energy, reduced the cost of energy savings when compared to the existing bulk data transfer strategies

In 2011, Jiamthapthaksin *et al.* [5] formulated the generic agglomerative clustering framework for the purpose of generalizing agglomerative clustering in the geo-referenced datasets (GAC-GEO) by using three plug-in components. The fitness function of the plug-in is maximized with the GAC-GEO agglomerates as it had the capacity to capture the notion of interestingness of clusters. This further enhanced the typical agglomerative clustering algorithms by using fitness functions support task-specific clustering, whereas generic neighboring relationships increase the number of merging candidates. This shows that the existing agglomerative clustering algorithms were considered as the specific cases of GAC-GEO. The proposed framework was

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evaluated on an artificial dataset and two real-world applications involving region discovery.

In 2017, Goel *et al.* [6] presented a dual algorithm; one was a hybridized version of two nature-inspired algorithms such as the Bat algorithm and Charged System for the purpose of better classification of the images and the second algorithm was the Clonal Selection Algorithm for Search for the purpose of feature extraction of geospatial big data as the geospatial feature extraction was crucial for remote sensing. Furthermore, the data set became more complex because of the usage of multispectral satellite images; this complexity further increased the number of dimensions for the classification problem. Moreover, this suggested that the proposed nature-inspired algorithm was good at classification of the land covers of satellite images. The evaluation of the efficiency of the proposed algorithms was made with the dataset of multispectral satellite images in order to prove that the proposed algorithm was better than the existing one.

In 2017, Shi *et al.* [7] suggested the affinity propagation (AP) algorithm as a novel machine learning algorithm for the purpose of classification of geospatial images related to the earth observations. The AP had a restriction access in handling large data. Moreover, the serial computer program took a long time to complete the AP calculation. Therefore multi-core and many-core computer architectures were accompanied by application accelerators by parallel combination of developing tasks and data levels; this was done for the purpose of guaranteeing and achieving scalable geocomputation. Moreover, for spatial cluster analysis, this AP algorithm was parallelized with the processing unit (GPU). This parallelization produced an optimal solution for the issues of big geospatial data processing and its broader impact for the GI Science community.

In 2018, Barik *et al.* [8] proposed a mist computing-based framework for the purpose of data mining and analyzing of the geospatial big data. The prototype here was built by utilizing the Raspberry Pi, an embedded microprocessor. The testimony of the developed *MistGIS* framework was carried by the preliminary analysis including K-means clustering and overlay analysis. The outcomes proved that mist computing had the capacity to assist fog and cloud computing and it too guaranteed the analysis of big data in geospatial applications.

## 10.3 PROBLEM DEFINITION

The literature has come out with several techniques for the EO based on geospatial data processing as shown in Table 10.1. However, they require more improvements because of lack of several features in data processing. Geo-reCAPTCHA [1] had generated geographic information from earth observation data and had the eligibility to distinguish between a human and a machine in case of data processing. It had reduced spam and viruses. The major drawbacks here were high data errors, low reliability and low quality. Moreover in a few cases it is very difficult to read data from clusters and requires more time to decipher. In case of the space–time prism model [2], common ontological problems were solved by template solutions. It had less spatial autocorrelation that essentially quantified the correlation parameters within

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itself through space and the spatial autocorrelation was positive, negative or zero to improve the quality of processing the data. The major challenges that need to be overcome here are less accessibility, less convergence and limitations in speed. With keyword-based matching algorithms [3] fast access and accurate service estimation was available; it also had pros as utilization of data demand patterns in different regions and time windows, and had the capacity to monitor EO data services from different geolocations. It had introduced the cloud-computing capabilities to facilitate EO data access and also optimized a cloud-computing data framework with spatiotemporal data access patterns. The cons of this method are that it needs deep learning technologies to improve access pattern prediction capabilities, had limitations in memory and resource allocation, more complex to cloud-computing infrastructures and the selection of appropriate cloud-computing services has become a barrier to cloud adoption in EO big data science. Moreover, in the case of the time-aware task scheduling algorithm [4] there was maximization in green energy usage and minimization in grid energy cost; it used all the wind power to transfer bulk data at each time slot and had reduction in energy cost. The major drawbacks were that it only focused on work load scheduling in a single green datacenter, and it had a more complicated scheduling and needs an optimal routing and bandwidth allocation for each task. Then, with the agglomerative clustering algorithms and density-based clustering algorithm [5] there was maximization in plug-in fitness function that captured the notion of interestingness of clusters, generic neighboring relationships increased the number of merging candidates; it had provided powerful region discovery capabilities and had demonstrated the capabilities of GAC-GEO in real-world case studies involving an earthquake dataset. It had drawbacks such as; with the round-robin approaches there was no improvement in fitness function, the selection of parameters were made without backtracking, it had no capability to identify arbitrarily shaped clusters, it had had high variance and high correlation with respect to non-spatial attribute(s). Furthermore, in the case of Swarm and artificial immune system-based intelligence techniques [6] it had advantages such as better classification of images, good quality of geospatial feature extraction and the spectral signature of each category is calculated using the training data. It had drawbacks such as high computational complexity and had no capacity to cover the land cover feature. Moreover with the Affinity propagation (AP) algorithm [7] there were advantages with GPU for spatial cluster analysis; it had the capacity to track the data that does not lie in a continuous space and had handled big data in an accurate way. It had challenges as low scalability, memory constraints, AP does not specify a predefined arbitrary number of clusters in advance so that dynamic scheduling was made and it also does not satisfy the triangle inequality. Moreover, with the K-means clustering algorithm [8] there was reduction in the latency period and it had increased throughput, it had adequate storage for data visualization and analysis, it had the capacity of local processing that had led to the reduction in data size, lower latency, high throughput, and power-efficient systems. All these were features of this algorithm and it had challenges in the case of cloud computing as it was not reserved for long-term analysis and it required efficient big data analysis and processing. In order to overcome all these challenges, there is a necessity to propose an optimal solution for geospatial big data processing.

**TABLE 10.1**
**Features and challenges of geospatial big data processing**

| Author [citation] | Adopted methodology | Features | Challenges |
|---|---|---|---|
| Hillen *et al*. [1] | Geo-reCAPTCHA model | • Distinguished between a human and machine during the problem-solving approach.<br>• Made the online polls more legitimate.<br>• Reduced spam and viruses. | • High data errors<br>• Less reliability and low quality in data processing<br>• Sometimes very difficult to read data from clusters<br>• More time consuming to decipher. |
| Kebler *et al*. [2] | Space–time prism model | • Common ontology modeling problems were solved<br>• Less spatial autocorrelation<br>• Spatial autocorrelation, was in positive, negative or zero to improve the quality | • Has constants with speed<br>• Less accessibility<br>• Less convergence |
| Xia *et al*. [3] | Keyword-based matching algorithm | • Fast access<br>• Accurate service estimation<br>• Monitor EO data services from<br>• Different geolocations. | • Had limitations in memory and resource allocation<br>• More complexity in cloud-computing infrastructures |
| Lu *et al*. [4] | Time-aware task scheduling algorithm | • Maximization of green energy usage and minimization of grid energy cost<br>• Uses all the wind power to transfer the bulk data at each time slot.<br>• Energy saving was high. | • Only focused on work load scheduling in a single green datacenter.<br>• More complicated scheduling<br>• Need optimal routing and bandwidth allocation for each task. |
| Jiamthapthaksin *et al*. [5] | Agglomerative clustering algorithms and density-based clustering | • Generic neighboring relationships increased the number of merging candidates<br>• Provided powerful region discovery capabilities<br>• High Accuracy | • No improvement in the fitness function<br>• Had no capability to identify arbitrarily shaped clusters<br>• Had high variance and high correlation |

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**TABLE 10.1 CONT.**

| Author [citation] | Adopted methodology | Features | Challenges |
|---|---|---|---|
| Goel *et al.* [6] | Swarm and artificial immune System-based intelligence techniques | • Better classification of images<br>• Geospatial feature extraction was clear and accurate<br>• The spectral signature of each category was calculated using the training data. | • High computational complexity<br>• Did not cover the land cover feature |
| Shi *et al.* [7] | Affinity propagation (ap) algorithm | • Graphics processing unit (GPU) was used for spatial cluster analysis.<br>• Had the capacity to track the data that do not lie in a continuous space.<br>• Handled big data in an accurate way. | • Low scalability<br>• Had limited memory space<br>• Did not satisfy the triangle Inequality. |
| Barik *et al.* [8] | K-means clustering algorithm | • Low latency<br>• High throughput<br>• Had adequate storage for data visualization and analysis<br>• Overhead on cloud server had reduced | • The cloud was not reserved for long-term analysis.<br>• Requires efficient big data Handling and processing |

## 10.4 METHODOLOGY

Figure 10.1 shows the proposed geospatial data classification model. Even though diverse application-related classification models can be developed using geospatial data, the main intention of this research proposal is to know about the kind of industry such as micro industries, macro industries, mid-scale industries, large-scale industries, small-scale and very large-scale industries that suit a specific location. This is because a multitude of factors influence the location decisions of firms and industries, including proximity to raw material supplies, availability of labor, good communications and nearness to markets. Here, geospatial data will be utilized for accomplishing the experiment, from which the X and Y co-ordinate are traced that is related to the latitude and longitude information, respectively. As there is a huge quantity of data it is given to the Hadoop framework for the purpose of handling that big data. Normally, the Hadoop framework is an Apache open-source framework written in java that allows distributed processing of large datasets across clusters of computers using simple programming models. Hadoop framework allows the user to

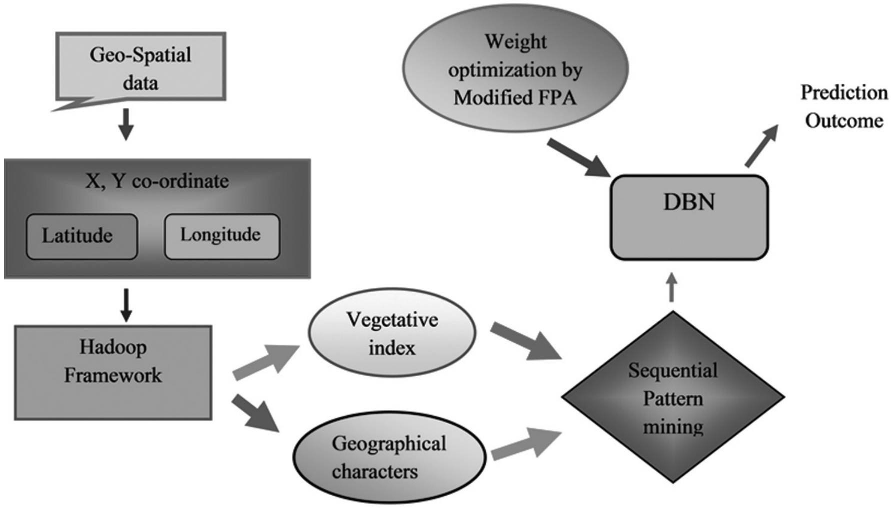


**FIGURE 10.1** Block diagram of Geospatial industrial data classification.

quickly write and test distributed systems with big data. Then, from the map reduced data, vegetation indices like simple ratio vegetative index, normalized difference vegetative index, Kauth–Thomas Tasseled cap and Infrared Index Transformation, as well as geographic location will be generated. Next to this data formation, sequential pattern mining will be performed, and those patterns will be assigned as the features. Furthermore, extracted features will be subjected to a deep learning architecture termed Deep Belief Network (DBN) [23], which predicts the type of industries a location suits. As a main contribution, the weight of DBN will be optimized by a renowned optimization algorithm called Modified Flower Pollination Algorithm (FPA), so that the classification accuracy will be maximum. FPA [24] is a metaheuristic algorithm inspired by the pollination process of flowers. In order to maximize prediction accuracy, the error between the predicted and actual outcome will be intended to minimize, which is considered the main objective function of this current research.

## 10.5 EXPECTED OUTCOME

The proposed prediction model will be carried out in the JAVA programming platform, and investigation will be carried out. In the analysis part, the performance of the proposed model will be compared over the existing models in terms of Type I and Type II measures.

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