Artificial Intelligence (AI) – based strategies for point cloud data and digital twins

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Abstract

Artificial Intelligence (AI), specifically machine learning (ML) and deep learning (DL), is causing a paradigm shift in coding practices and software solutions across diverse fields. This study focuses on harnessing the potential of ML/DL strategies in the geospatial domain, where geodata possesses characteristics that align with the concept of a “lingual manuscript” in aesthetic theory. By employing ML/DL techniques, such as feature evaluation and extraction from 3D point clouds, we can derive concepts that are specific to software, geographical areas, and tasks. ML/DL-based interpretation of 3D point clouds extends geospatial modelling beyond implicit representations, enabling the resolution of complex heuristic-based reconstructions and abstract concepts. These advancements in artificial intelligence have the potential to optimize and expedite geodata computation and geographic information systems. However, ML/DL encounters notable challenges in this domain, including the need for abundant training data, advanced statistical methods, and the development of effective feature representations. Overcoming these challenges is essential to enhance the performance and efficacy of ML/DL systems. Additionally, ML/DL-based solutions can simplify software engineering processes by replacing certain aspects of current adoption and implementation practices, resulting in reduced complexities in development and management. Through the adoption of ML/DL, many of the existing explicitly coded GIS implementations may gradually be replaced in the long term. Overall, this research illustrates the transformative capabilities of ML/DL in geospatial applications and underscores the significance of addressing associated challenges to drive further advancements in the field.

Keywords: deep learning (DL); geospatial AI; geospatial digital twin; machine learning (ML); point cloud data

Introduction

Artificial Intelligence (AI) transforms how IT solutions are crafted, created, and managed. AI is not restricted to a few application domains; it permeates mainly all fields and businesses. AI has a significant impact as an acquisition of broad sense technologies because it can reshape prospects both for growth in the economy...
and for a firm’s profitability (Purdy and Daugherty, 2017). Critical questions for geospatial domains include how AI can be explicitly practiced or must be typically designed for spatial analysis (Janowicz et al., 2020). A description of spatially explicit AI that uses advances in methods and technique cultures to embrace the concept of more insightful geographical data as well as strategies, frameworks, and services to a wide range of regression tasks. This emerging research practice, known as geospatial artificial intelligence, will specifically enhance and generate innovative methods for geospatial data systems by combining advancements in spatial science, machine learning and AI, data collection, and high-performance data processing to given circumstances from spatial big data (VoPham et al., 2018).

The term AI raises a series of concepts and theories, such as defining human, natural, or broad-sense intelligence. Simply put, the most common misunderstanding about artificial intelligence starts with the most popular myth regarding innate intelligence. The common myth is that intelligence has only one dimension. In general, AI often conjures associations and perceptions like imitating or surpassing human thinking. If AI is viewed sensibly as a scientific advance, it will magnify the human psyche rather than replace it, just as any tool does. In general, there is no clear distinction between AI and non-AI tech. Consider an autopilot steering an aircraft: it was initially perceived as AI, but it has now become a popular functioning technological element. Once AI becomes widely used, it is often no longer regarded as being such. In that context, the word “AI” refers to innovation pushing current tech limits. In this article, we discuss AI together in a geospatial context and concentrate on Machine Learning and Deep Learning capabilities for point cloud data (Haenlein and Kaplan, 2019).

Several AI technologies and disciplines are used to build AI-based IT systems, including machine learning, deep learning, natural language processing, computer vision, and robotics. These technologies create intelligent and autonomous systems that perform various tasks, including decision-making, prediction, and pattern recognition. From the software engineering standpoint, several techniques, and specializations (Fig. 1) are required to develop AI-based IT solutions.

Point Cloud Data

Point cloud data is a type of 3D data representing an object’s external surface. It is composed of a set of data points in three-dimensional space, each representing the position of a specific point on the object’s surface. The position of each point is typically characterized by its x, y, and z coordinates (Richter and Döllner, 2013). Point clouds are commonly used in computer vision and robotics applications to represent 3D models of objects, surfaces, and environments. They can be generated using various methods, including laser scanning, structured light scanning, and stereo vision.
Point clouds can be used for various purposes, including 3D modelling, surface reconstruction, object recognition and classification, and scene understanding. They are beneficial for tasks that require the accurate representation of 3D geometry, such as robot localization and navigation. They are often combined with other types of 3D data, such as meshes or volumetric data. Point cloud deep learning has emerged as a powerful approach, demonstrating notable achievements in various tasks including unsupervised representation learning, generating shapes, upsampling and completing point clouds, and matching points between different clouds (Xiao et al., 2022).

**Digital Twins**

A digital twin refers to an exact virtual representation of physical assets, processes, and systems. It involves digitalizing and storing operational data, topography, spatial information, shape details, movement characteristics, and operational rules pertaining to both the replicated system and the corresponding target system on a computer (Meierhofer et al., 2021; Pang et al., 2021). In recent years, the term “digital twin” has gained prominence within the engineering field, although the concept itself has been applied across various professional domains for quite some time. An illustrative example of digital twin utilization dates back to NASA’s Apollo 13 mission in 1970. During this mission, real-time malfunction data from the spacecraft employed for lunar exploration were transmitted via communication channels from the near-moon spaceship to a ground-based simulator. Subsequently, a virtual experiment was conducted using the simulator to examine the causes of the failure and develop methods for restoring normal operation. This case serves as a notable instance showcasing the early application of a digital twin in practice (Rosen et al., 2015; Boschert and Rosen, 2016). Michael Grieves, a renowned researcher in the field of product lifecycle management, is widely credited with originating the terminology digital twin (Grieves and Vickers, 2017). Digital twins are made up of 3 parts: physical entities in the physical world, virtual approaches in the digital world, and corresponding data that connects the two worlds (Qi and Tao, 2018). While sensors can handle the connection between the two, virtual models can be derived from their physical equivalents. 3D point clouds, for instance, are utilized to generate 3D interior models that are significant elements of real-time BIMs, along with sensor nodes and Internet of Things systems (Khajavi et al., 2019). Researchers are leveraging technologies like GIS, Point Cloud Data, Finite Element Models, and Machine Learning techniques to advance Infrastructure Digital Twins (IDTs). For interoperability solutions, it is suggested that edge-based approaches work well for simple IDT architectures, while server-based solutions can be employed for more complex IDT architectures, albeit with potential adaptability issues (Naderi and Shojaei, 2023). In the construction industry, digital twins have been used in various scenarios, which can be summarized in Table 1. These cases can be broadly classified into two distinct categories: the first category encompasses the specific fields where digital twins are employed, while the second category pertains to the implementation process of digital twins. Please refer to Table 1 for a comprehensive overview of these cases.

**Attributes**

A point cloud data is a collection of 3D data in a specified reference frame that can be described as follows:

- Irregular
- Incomplete
- Per-point attribute
- Discretely represented
- Uniformly represented
- Ambiguity
- Massive
The lack of any conceptual or semantics-related information characterizes point cloud data, a basic component of geospatial data. Point cloud data is a simple, unsorted set of 3D points. Nevertheless, the absence of configuration and accessibility is both strength and weakness (Gross and Pfister, 2007). As a result, there is a need for solutions to enable us to enhance 3D point clouds with data.

### Table 1. Comprehensive overview of implementation process of digital twins

<table>
<thead>
<tr>
<th>Field</th>
<th>Data Capture</th>
<th>Application</th>
<th>Services</th>
<th>Year</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>City planning</td>
<td>QR Codes, IPC, Sensors</td>
<td>3D Models</td>
<td>Simulation optimization</td>
<td>2021</td>
<td>(Shah et al., 2021)</td>
</tr>
<tr>
<td>Infrastructure</td>
<td>GIS, Sensors</td>
<td>BIM</td>
<td>Monitoring</td>
<td>2020</td>
<td>(Lu et al., 2020)</td>
</tr>
<tr>
<td>Infrastructure</td>
<td>Space management system, Sensors, QR codes</td>
<td>BIM</td>
<td>Identification of anomalies in repair and operation</td>
<td>2021</td>
<td>(Lee et al., 2021)</td>
</tr>
<tr>
<td>Infrastructure</td>
<td>Geospatial datasets</td>
<td>BIM</td>
<td>Monitoring</td>
<td>2021</td>
<td>(Zhuang et al., 2021)</td>
</tr>
<tr>
<td>Infrastructure</td>
<td>AI, Sensors, Thermal cameras</td>
<td>BIM, Thermography map</td>
<td>Energy planning</td>
<td>2021</td>
<td>(Kaewunruen et al., 2021)</td>
</tr>
<tr>
<td>Architecture</td>
<td>Sensors</td>
<td>3D Models</td>
<td>Architecture for a physical system</td>
<td>2019</td>
<td>(Borth et al., 2019)</td>
</tr>
<tr>
<td>Infrastructure</td>
<td>Drawing data, Geology data</td>
<td>BIM</td>
<td>Greenhouse gas emission, Cost data, Time schedule</td>
<td>2019</td>
<td>(Kaewunruen and Lian, 2019)</td>
</tr>
<tr>
<td>Infrastructure</td>
<td>Electrical current magnitude</td>
<td>3D Models</td>
<td>Stability of structure</td>
<td>2013</td>
<td>(Majumdar et al., 2013)</td>
</tr>
<tr>
<td>Architecture</td>
<td>LiDAR</td>
<td>3D Models</td>
<td>Digital twin models for city</td>
<td>2020</td>
<td>(Xue et al., 2020)</td>
</tr>
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<td>Infrastructure</td>
<td>LiDAR</td>
<td>3D Models</td>
<td>Digital twin models for structures</td>
<td>2022</td>
<td>(Luis Lugo et al., 2022)</td>
</tr>
<tr>
<td>Infrastructure</td>
<td>Sensors</td>
<td>3D Models</td>
<td>Optimisation</td>
<td>2022</td>
<td>(Liu et al., 2022)</td>
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<tr>
<td>Infrastructure</td>
<td>LiDAR</td>
<td>BIM</td>
<td>Simulations</td>
<td>2022</td>
<td>(Zhao et al., 2022)</td>
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<tr>
<td>Infrastructure</td>
<td>LiDAR</td>
<td>BIM</td>
<td>Monitoring, Optimization</td>
<td>2018</td>
<td>(Tao et al., 2018)</td>
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<tr>
<td>Environment</td>
<td>IoT Database</td>
<td>Disaster Management</td>
<td>Simulations</td>
<td>2022</td>
<td>(Kwon et al., 2022)</td>
</tr>
<tr>
<td>Infrastructure</td>
<td>GIS, Geospatial Datasets</td>
<td>3D Models</td>
<td>Digital twin models</td>
<td>2022</td>
<td>(Jiang et al., 2022)</td>
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</tbody>
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**Point Cloud Data Time Series**

A point cloud data time series is a sequence of point cloud data sets collected over time; a time series is a sequence of data points collected at regular intervals. 3D point clouds are being captured and processed regularly for many applications. For illustration, if a monitoring system captures its way to attain every second, the result is a stream of 3D point clouds. These sets are expected to act in accordance if 3D point clouds are collected or developed at varying points with intersecting geospatial areas. In some ways, the gathering of 3D point clouds denotes a 4D point cloud. The high degree of redundancy in 3D point cloud time series must be utilized to ensure effective monitoring, refining, encoding, and backup, for illustration, by isolating static from dynamic systems. Additionally, the configuration can enhance the accuracy and reliability of 3D point cloud conceptions and linked forecasting.
Point cloud time series can track changes in an object or environment over time. For example, a time series of point cloud data could be used to track the movement of an object, such as a robot or a vehicle, or to monitor changes in an environment. It can also be used to train machine learning algorithms for tasks such as object classification or segmentation. It is possible to create a model that recognizes and classifies objects or features within the point cloud data by preparing a machine learning algorithm on a series of point cloud data collected over time.

**Computer Vision**

As the use of Unmanned Aerial Vehicle (UAV) remote sensing for acquiring Digital Twin data becomes more prevalent, the automated comprehension of visual data becomes increasingly crucial. This has led to a stronger correlation between computer vision and deep learning, as they work hand in hand to tackle this challenge. Computer vision is a multidisciplinary area of study that originated in the 1960s, encompassing various fields and approaches to understanding and enabling machines to perceive and interpret visual information (Dong and Catbas, 2021). The initial computer vision system aimed to derive shape information from objects by considering potential objects, backgrounds, and areas with unpredictable patterns or irregularities (Voulodimos et al., 2018). As image processing advanced, computer vision expanded its scope to tackle more intricate perceptual challenges. These included tasks like facial recognition (Zhang et al., 2016), pedestrian detection (Zhang et al., 2019), and car detection (Guo et al., 2022), which demanded greater sophistication in visual analysis. The recent advancements in computer vision technology have predominantly been driven by the adoption of deep learning algorithms, such as artificial neural networks (ANNs) and convolutional neural networks (CNNs). These algorithms have demonstrated remarkable success in constructing perceptual systems capable of addressing intricate visual problems with a high level of complexity (Wu et al., 2018). Artificial neural networks (ANNs) serve as a broad category that encompasses both deep neural networks (DNNs) and shallow neural networks (SNNs). The primary distinction between these networks lies in the number of hidden layers they employ. DNN architectures typically consist of many hidden layers, potentially reaching hundreds, while SNNs are constrained to only a few layers (Gorokhovatskyi and Peredrii, 2018). Computer vision and deep learning find extensive applications across various domains, including general image classification (Yeum et al., 2018) and automated transportation systems (Simonyan and Zisserman, 2014). Moreover, numerous research endeavours leverage computer vision and deep learning techniques in the context of civil infrastructure emergency management (Cheng et al., 2023). Through the analysis of potential risks, decision makers have the ability to proactively take preventive measures before experiencing catastrophic consequences (Dogan et al., 2021). The conventional process of anomaly detection relies heavily on manual intervention by skilled experts, and it encounters difficulties in systematically integrating different data sources, leading to delays in identifying deviations from normal patterns (Motawa and Almarshad, 2013). A challenge associated with anomaly detection processes relying on Digital Twins is that the presence of extensive facility data can result in a significant computational burden, impacting the real-time performance of the detection system (Jung and Sundstrom, 2017; Chen et al., 2023). The most recent approach for anomaly detection in building heating, ventilation, and air conditioning (HVAC) systems introduces a method that focuses on data feature extraction and selection. This novel approach aims to enhance the efficiency of anomaly detection, enabling real-time and automated asset monitoring during daily operation and maintenance management (Xie et al., 2023). Deep neural networks (DNNs) applied to computer vision have demonstrated remarkable capabilities in accurately classifying and segmenting 3D point cloud data (Diab et al., 2022). Nevertheless, the intricate architectures and numerous parameters of these networks demand substantial computational resources, making them less suitable for real-time applications in resource-limited environments. This limitation applies to both the training and inference stages (Lei et al., 2020).
Deep learning applied to point cloud data

Point clouds are a prevalent form of 3D data, and several deep learning models have been developed to handle them. One common approach involves transforming the point cloud into a consistent voxel grid and utilizing convolutional neural networks (CNNs) designed for volumetric representations, as described in (Maturana and Scherer, 2015; Wu et al., 2015 and 2016; Brock et al., 2016; Ruizhongtai Qi et al., 2016). Although transforming point clouds into voxel grids enables the utilization of regularly structured data for deep learning, this approach suffers from computational intensity, which imposes limitations on the point cloud resolution. To address the issue of voxel grid resolution, alternative methods have been suggested. These include employing octree structures with field probing filters or leveraging the sparsity of the problem through voting schemes (Li et al., 2016; Riegler et al., 2016; Wang et al., 2017). Nonetheless, the limited resolution of voxel grids continues to impose restrictions on the scale of point clouds that can be effectively processed.

Instead of relying on voxel grids, recent advancements have introduced novel techniques to directly handle unordered point sets. These methods have demonstrated impressive outcomes in point cloud classification, comparable to approaches that classify volumetric objects and meshes (Maturana and Scherer, 2015; Wu et al., 2015).

A new approach for classifying point clouds yields competitive results compared to current methods that operate directly on raw point cloud data. This involves automatically transforming the input point cloud to one or multiple depth images. These images can then be combined and classified using a dedicated CNN classification module. This strategy leverages the exceptional performance of CNNs when applied to image-based tasks and the abundant availability of training data for such networks (Roveri et al., 2018).

Practicability of Machine Learning (ML) / Deep Learning-Based (DL) Approach

ML models/algorithms acquire knowledge from data in situations where the simulated phenomenon is poorly explained. This key feature explains why it is widely applied, including in geospatial data use (Kanevski et al., 2009). Because of the lack of structure, order, and semantics, as well as the inherent discontinuity, imperfection, and ambiguity, 3D point clouds are difficult applicants for prescriptive and analytic coding. Even so, their properties enable us to apply appropriate Machine Learning/Deep Learning to point cloud data such as Big Data, Fuzziness, and Semantics.

ML/DL support provides domain-specified and app-specified information in the case of 3D point clouds, usually through point categorization, point cloud classification, object recognition, and structure reconfiguration. ML/DL-based strategies have considerably less complexity of the algorithm than traditional procedural-like, heuristic, or empiric-based algorithms because they rely on broad-sense AI structures with higher reliability and levels of innovation. The personalization consists in locating suitable instruction and trial data. The resiliency of ML methods is a critical issue because ML models have always been susceptible to adverse illustrations created by implementing slight, carefully selected instabilities to inputs that end up causing unforeseen misclassifications (Rozsa et al., 2016).

Aesthetic Theory

The Aesthetic Theory (Allamanis et al., 2018), studied in formal language recognition and software algorithms, contributes to better comprehending why ML and DL methodologies are efficient tools for analyzing and evaluating 3D point clouds. In a broad sense, a critical strategy to ML and DL is determining whether the problem situation domain matches up to or has mathematical properties comparable to massive natural language corpora (Jurafsky and Martin, 2000).

3D point cloud data, in a pattern of everyday communication and geospatial contexts, are eventually redundant, despite the endless variety they might very well display. In some ways, 3D point clouds are just “spatial expressions” that can be modeled statistically. As a result, 3D point clouds represent 3D point cloud embedding, to which Machine Learning techniques can be implemented by leveraging numerical distributional characteristics approximated over reflective point cloud datasets.
Pursuing the explanatory framework established for software development (Hindle et al., 2012), Machine Learning/Deep Learning-centric aesthetic theory for 3D point clouds is as follows:

3D point clouds have the potential to be intricate, rich, and robust in theory; the reality is that the 3D point clouds captured or generated within geospatial domains tend to exhibit lower complexity, expressiveness, and repetitiveness. Their observable statistical characteristics can be acquired in numerical language models and used to evaluate spatial information.

However, ML and DL strategies must be customized to the properties of 3D point clouds. Most pertinently, standard deep neural networks (NN) require a common framework in their input information, whereas point clouds are principally random: point locations are steadily spread in space, and any variation of their sorting does not affect spatial variability (Wang et al., 2019).

Machine Learning/Deep Learning-Based Point Cloud Interpretation

3D point clouds are a low-cost raw data source for building the foundation for geospatial digital twins at all levels. However, they are geometrical data without any systemic or semantic data about the object classes they depict. Inspired by aesthetic theory, ML and DL could be used to evaluate and assess that data and to supply effective methods for discrete infrequent, imperfect, and uncertain data from an extensive series of what 3D point clouds are.

Interpretation Theory

The interpretation concept from programming languages is utilized in the ML/DL-based computation of 3D point clouds. However, steps that gather original data into elevated characterizations are optional for analysis tools and semantics in that framework. The Point Net NN, for illustration, actively uses point clouds and quite well recognizes the factorization stability of points in the input to generate information and gives architecture for various applications from object recognition and part segmentation to semantic parsing.

Applications or systems that offer 3D point cloud geospatial data specify the number of characteristics to be derived and the spatial extent to be trawled. The accessible showcase types are calculated by how the Machine Learning and Deep Learning sub-systems were previously instructed. The analysis procedure involves initiating an evaluation to obtain the desired outcomes without the need for pre-processing or pre-evaluating 3D point clouds. Additionally, there is no requirement for intermediate representations of the data. In this approach, the interpretation operates directly on the raw point cloud data as needed. The classical geoprocessing workflow is compared to the workflow enabled by ML/DL-Based 3D point cloud interpretation. While traditional workflows generate precise, detailed, and semantic information with well-defined depictions, ML/DL-based workflows operate on original data, exporting the desired features using training sets (Figures 2 and 3).

Figure 2. The traditional workflow focused on 3D reconstruction, modeling, and object derivation

Figure 3. Workflow for machine learning and deep learning focusing on 3D point cloud interpretation
The ML/DL generator that deploys those inputs must have the following core capabilities:

- **Point classification**: Classifications are calculated and appended as per-point characteristics and the possibility for this group assessment based on specified point classes (e.g., grassland, buildings, irrigation, roads) (Roveri et al., 2018).

- **Point cloud segmentation**: As a fundamental procedure for 3D point clouds, segmentation aids in lowering disintegration and segregating substantial point clouds. It is based mainly on recognizing 3D geometrical characters such as edges, planar facets, or curves. In comparison, ML and DL enable us to benefit from conceptual signals and attributes located in 3D point clouds (Wang et al., 2019).

- **Shape recognition**: Recognizing 3D surroundings requires the recognition of forms. To understand them, a consolidated 2D–3D strategy of creating 2D visuals from 3D point clouds analyzed by image analysis is used (Stojanovic et al., 2019).

- **Object classification**: Most applications require element data to be derived from 3D point clouds, such as road signs and lampposts. Convolutional neural networks (CNN) centered on parametric depictions or CNNs based on the multi descriptions are widely used to this extreme and are predicated on classification and partitioned 3D point clouds (Qi et al., 2016).

The non-uniform sample size concentration observed in 3D point clouds is a significant challenge for ML/DL-based learning. Because learning methods in closely packed information may not sum up to sparingly tested areas, Qi et al. (2016) proposed a hierarchical CNN that works on layered portions of a source point set. As a result, models trained on sparse point clouds may fail to recognize perfectly alright local features (Ruizhongtai Qi et al., 2017).

We can apply standard evaluation elements for 3D point clouds using ML/DL perception. Because no transitional characterizations are needed, the analysis results are only generated when demanded, yet they are only calculated for the region identified by the assessment.

Among the benefits of this method are the following (Döllner, 2020):

- **Configuration**: Numerous attribute kinds can be expected using ML/DL data for training and feature set definitions. The primary, domain-independent process offers a greater degree of customizability for it.

- **Computation on a service basis**: Scalability is achieved using relatively low and elevated facilities and add-ons, which can be charted to a service-oriented layout and configurable components (e.g., GPU clusters).

- **Demand-based computation**: Downstream capabilities allow calculation on demand. Many categories can be interpreted instantaneously (for example, object recognition from point clouds for surveillance).

- **Processing Raw Data**: No 3D frameworks or transitional characterizations have been selected before or constructed. As a result, the technique works well enough for large or time-varying 3D point clouds. Because raw data is fed explicitly into the ML/DL methods, the precise accuracy of the original information is never lowered.

- **Storage Efficient**: Vast 3D point cloud capacity and managing, which include time-variant versions, can be enhanced separately because assessment only demands rapid spatial entry to point cloud components.

### Artificial Intelligence for Geospatial Digital Twin

A critical usage in digital modifications is for digital twins, which are digital depictions and replicas of a living or non-living material object’s main characteristics, behavior, and forms (Jurafsky and Martin, 2000). The structure of data collected for geospatial digital twins relying on formally defined 3D model conceptual
frameworks is a labor-intensive and error-prone procedure. For illustration, 3D virtual city models with high levels of detail (LoD), such as LoD3 or LoD4, as 3D imaging methods and the simulation models must deal with imprecise, incomplete information and usually cannot deal with the cases that are not supplied in the simulation models scheme (Löwner et al., 2016). When reconstructing a 3D framework, there are instances where the resulting representation may not accurately capture poorly recorded, unconventional, or unclear entities. This limitation persists even when utilizing advanced mathematical concepts or decent algorithms.

3D point clouds depict original data of geospatial units in a well-defined, reliable, and straightforward manner, particularly for spatial surroundings such as indoor areas, BIMs, and towns (Stojanovic et al., 2019). ML/DL-based perception can analyze and arrange 3D point clouds effectively and successfully without being constrained by explicitly defined modeling semantics. Overall, it adaptively produces semantics on demand and the fly, thereby mending one of the most serious shortcomings of 3D point clouds: a need for more framework and definitions. There are virtually no restrictions on the forms of 3D shapes, systems, or occurrences that can be recognized and derived using ML/DL-based 3D point cloud analysis. In addition, there are spatial mapping-based methods available that convert irregular 3D point clouds into regular representations, enabling easier processing using conventional 2D networks (Zhang et al., 2023).

Conclusion

Artificial Intelligence is transforming coding normative and software solutions across all application areas. The data characteristics in the geospatial sphere are especially suited for ML/DL strategies because geodata appears to fit into the idea of a “lingual manuscript” as depicted in the sense of aesthetic theory. For illustration, ML/DL-based evaluation and extraction of features from 3D point clouds can be used to derive software-specific, area-specific, and task-specific concepts.

Overall else, ML/DL-based perception of 3D point clouds allows us to move beyond implied geospatial modeling and, as a result, resolve intricate, heuristic-based recreations and model-based abstract concepts. Artificial intelligence can be used to optimize and speed up frameworks for geodata computation and geographic information systems in this regard. In the field of ML/DL, significant challenges arise due to the requirement for extensive training data, advanced statistical techniques, and the development of effective feature representations. This highlights that ML/DL problems often require a large amount of data for training models effectively. These problems demand sophisticated statistical methods to analyse and draw meaningful insights from the data. Another crucial aspect is the creation of accurate and informative feature representations, which are crucial for capturing the underlying patterns and structures in the data. Addressing these challenges is essential to enhance the performance and effectiveness of machine learning and deep learning systems.

Lastly, ML/DL-based remedies simplify the software engineering aspect. Large portions of today’s adoption and implementation (often grown with significant amounts of so-called technical debt) will be partially replaced by Machine Learning/Deep Learning, which has far fewer software development and management intricacies. Most fuzzy, primarily performed analysis procedures, which are extremely difficult to characterize and setup, can be relocated in this manner. As a result, ML/DL-based practices have the potential to take up many of today’s explicitly coded GIS adoption and implementation in the long-term.

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Authors’ Contributions

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All authors read and approved the final manuscript.

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