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A Review of the Integration Between Geospatial Artificial Intelligence and Remote Sensing

Abeer A. Mohamad Alshiha

University of Mosul
Mosul, Nineveh, 44003, IRAQ

*Corresponding Author: Abeer A. Mohamad Alshiha

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ABSTRACT: Experts have extensively explored the advantages and applications of modern artificial intelligence (AI) algorithms across various domains. Geomatics data processing is no exception, as AI offers significant opportunities in this field. However, understanding how AI can be customized or developed to meet the unique requirements of geomatics data is crucial. Integrating AI techniques into geomatics has given rise to Geospatial Artificial Intelligence (GeoAI), a novel approach to uncovering geographic information. Nevertheless, there remains a shortage of comprehensive research on the specific applications of AI in geospatial contexts. Consequently, this study aims to establish AI-based methodologies for the analysis and interpretation of complex geomatics data, bridging existing gaps, and elucidating the connections between AI principles and geomatics data. This paper delves into the innovations and tools employed for data acquisition in geomatics, focusing on RGB images, thermal images, 3D point clouds, GPS coordinates, and hyperspectral/multispectral images. Subsequently, we elucidate how AI techniques have successfully extracted valuable insights from geomatics data. Furthermore, we present various practical scenarios where AI has been deployed and the specific methodologies employed for each case. Through this exploration, we aim to highlight the immense potential of AI in geomatics and stimulate future research endeavors.

Keywords: Remote Sensing, Algorithm Models, Spatial Data, RGB-D Cameras, Infrared Cameras, Digital Photogrammetry, Terrestrial Laser Scanning, GNSS Positioning, Artificial Intelligence.

1. INTRODUCTION

Remote sensing is the process of collecting information about an object, area, or phenomenon without direct physical contact. This is typically achieved using sensors mounted on platforms such as satellites, aircraft, or drones to detect and record data from a distance. Remote sensing enables the observation and measurement of various characteristics of the Earth's surface or atmosphere, including but not limited to land cover, vegetation health, temperature, and atmospheric conditions [1].

The sensors used in remote sensing capture data in the form of images or digital signals across the electromagnetic spectrum. These data can then be analyzed to extract valuable information for various applications, such as environmental monitoring, resource management, agriculture, urban planning, disaster assessment, and scientific research. Remote sensing technology is crucial in acquiring detailed and large-scale information about the Earth, facilitating informed decision-making and understanding of our planet's dynamic processes [2].

Geomatics is a multidisciplinary field specializing in automated processing and managing complex 2D or 3D data. It entails the collection, storage, integration, modeling, and analysis of spatially referenced information in digital formats with high accuracy and consistency [1]. Geomatics uses various tools and data collection techniques, including remote sensing, to effectively handle large volumes of data in an interdisciplinary and interoperable manner. This field encompasses various sub-disciplines, such as surveying, geodesy, geology, photogrammetry, and cartography, which are all interconnected to facilitate the acquisition and representation of data [1].

Geomatics encompasses a wide range of data data formats derived from diverse systems and platforms. These include RGB, multispectral, hyperspectral, and thermal images, along with trajectories and point clouds acquired through remote sensing methods. The processing of this data often relies on manual or semi-automatic procedures, as full automation has not yet achieved the desired standards of reliability and accuracy. After processing the data, the georeferenced information is meticulously documented, manipulated, displayed, and stored within geographic information systems (GIS) or generic databases. However, the emergence of big data has necessitated the use of specialized computational techniques such as artificial intelligence (AI), machine learning (ML), and deep learning (DL) for effectively analyzing and harnessing the vast wealth of information it contains [2][3].

 *Corresponding author: author@organization.edu.co

One significant advantage of AI is its capability to recognize meaningful patterns within intricate and non-linear geomatics data without the need for explicit, pre-programmed instructions. The efficacy of DL and AI algorithms has been demonstrated in various geomatics applications, particularly remote sensing [4]. Depending on the nature of the collected data, diverse AI techniques are put forth, encompassing classification, semantic segmentation, and object detection [4].

Remote sensing is pivotal in integrating geomatics and artificial intelligence (GeoAI). By utilizing sensors on satellites, aircraft, and drones, remote sensing gathers valuable information about the Earth's surface without direct contact. This diverse data includes optical, multispectral, hyperspectral, thermal, and LiDAR data. GeoAI and geomatics rely heavily on remote sensing data as input for AI and ML algorithms. This enables them to analyze, interpret, and derive meaningful patterns and insights from vast geospatial information [5]. Its roles encompass data acquisition over large areas, feature extraction, change detection, image classification, semantic segmentation, object detection, environmental monitoring, disaster management, and precision agriculture. By harnessing remote sensing data, GeoAI revolutionizes environmental management, disaster response, precision agriculture, and various other fields, paving the way for well-informed decision-making and promoting sustainable development [5].

The article explores the fascinating realm of GeoAI, delving into various algorithms and models that contribute to this field. It emphasizes the fundamental role of geomatics as a rich source of data. The content covers various topics, from RGB-D cameras to infrared cameras, digital photogrammetry, terrestrial laser scanning, and remote sensing with multispectral data and hyperspectral data. Additionally, the article discusses the significance of Global Navigation Satellite System (GNSS) positioning. By examining these technologies and methodologies, the article aims to provide insights into the diverse aspects of GeoAI and its applications in the geospatial domain. The concluding section summarizes the key findings and implications of the discussed content.

2. ALGORITHMS AND MODELS FOR GeoAI

AI aims to emulate the functioning of the human brain and develop advanced algorithms based on acquired data. The development of AI and its subsets, such as ML and DL, has ushered in significant transformations in data analysis [6]. ML and rule-based tools were originally designed to extract meaningful patterns from data. However, with the advent of multimedia big data, the adoption of DL approaches has become more prevalent. DL offers increased efficiency and capability in handling the vast datasets generated by modern applications, effectively addressing the complexities inherent in analyzing and interpreting geomatics data. In contrast to traditional ML models, DL models, particularly Deep Neural Networks (DNNs), can learn and adapt continuously, rendering them highly effective in real-world tasks [3].

DNN structures are increasingly employed in geomatics due to their ability to extract essential features from data. Despite being initially considered "black box" operators, the need for DNNs to be interpretable and understandable is increasing [7]. Geomatics tasks solved using ML and DL models can be summarized as follows:

- Clustering [8].
- Classification and Prediction [9].
- Object Detection [10].
- Segmentation [11].
- Part Segmentation [12].
- Semantic Segmentation [13].

These tasks encompass various applications. DL models have proved highly effective in extracting meaningful information and patterns from geomatics data, leading to significant advancements in various domains [13].

Clustering involves learning a target function (f) that maps an input vector (x) to one of the predefined labels (y). The objective is to build classification models with a strong predictive ability to accurately predict class labels for new data [14].

Object detection is the task of identifying and categorizing instances of objects (e.g., people, animals, or vehicles) within an image. It forms the basis of various computer vision applications, including event segmentation, image captioning, and object tracking. Object detection can be classified as "general object detection," which identify multiple types of objects using a single framework or "detection applications," which recognize objects of a specific class under certain conditions. Models for object location can be additionally separated into two classes: two-stage and one-stage finders [14].

Image segmentation is a fundamental research area with applications in various fields, such as industrial signal processing and biomedical diagnostics. It entails dividing a picture into isolated areas (portions) that possess comparable qualities, such as splendor, variety, and surface. The division is implemented to remove objects of interest from a picture, which is an intricate issue due to the presence of different semantic articles [15].

Recent studies [15] have shown that DL approaches have demonstrated remarkable performance in object instance segmentation, covering rigid and non-rigid objects. Image division breaks down the parcel picture into various areas, each of which corresponds to a particular item. Semantic segmentation surpasses mere image segmentation by dividing the image into regions and assigning a class label to each identified region. Semantic segmentation involves labeling and defining sets of pixels in an image, such as identifying animals, people, or buildings.

Semantic segmentation is a valuable alternative to object detection, especially for identifying intricately shaped objects. In contrast to object detection, which requires objects to fit within bounding boxes, semantic segmentation enables the identification of objects at the pixel level, making it effective for objects with complex shapes [15].

Furthermore, semantic segmentation has gained importance in understanding 3D scenes, particularly in the context of point clouds. AI-driven approaches have emerged to recognize objects in 3D scenes automatically, leading to various methods proposed in recent years [16].

3. GEOMATICS: A FUNDAMENTAL SOURCE OF DATA

This section will try to classify the different kinds of sensors utilized for information procurement and portray their quality. The grouping depends on obtaining gadgets and information highlights, considering yield information, organizing, dynamic/uninvolved sensors, and setting off. It is critical to note that this survey does not include all geomatics strategies in favor of focusing on sensors that generate complex information that necessitate factual learning-based approaches.

Geomatics surpasses basic distance and point estimations by managing multiresolution geospatial and spatio-worldly information for different logical, design, and regulatory applications. This incorporates perception and estimation of different spatial, unearthly, and worldly goals, for example, computerized symbolism with various pixel sizes and ghastly groups [17].

Traditional surveying has evolved with new technologies; positioning and navigation can now be achieved using various devices. Geographic mapping, once requiring complex calculations, is now facilitated by geospatial information or GIS. Digital images from various sensors, including satellites and smartphones, serve diverse purposes, from environmental assessment to virtual simulations [17].

Sophisticated digital processing, portable setups, and readily available equipment such as Terrestrial Laser Scanners (TLS) have replaced traditional surveying methods and photogrammetric transformation algorithms. High-resolution satellite and aerial images enable regional-level analysis and land use classification, while advanced techniques such as LiDAR and radar pulse describe shapes [18].

Contemporary acquisition tools are now able to capture highly intricate, architectural-scale objects. Despite their affordability, equipment such as cameras, compact robots, and depth sensors can effectively execute modeling tasks, albeit with certain degree of compromised precision. To achieve higher levels of accuracy, georeferencing these complex models often necessitates the use of GNSS receivers or TLS technology [19].

Geomatics is utilized across various domains, encompassing the natural environment, quality of life in rural and urban settings, disaster prediction, security measures, recovery efforts, and the documentation and conservation of archaeological sites. It can address a multitude of scales. While it is not a one-size-fits-all solution, integrating diverse information and techniques is the most effective approach for 3D analysis, positioning, and feature extraction [19].

3.1 RGB-D CAMERAS

Before the release of Microsoft Kinect in November 2010, acquiring depth data from images was a complex and costly process. Recent efforts have capitalized on the growing prevalence of depth sensors and the advancements in ML and DL [20].

RGB-D cameras provide color information and depth map reconstruction capabilities [6]. Depth images add a third dimension, enhancing various computer vision tasks such as background removal, scene segmentation, object and person tracking, 3D environment reconstruction, body pose recognition and gesture-based interfaces.

Depth maps are obtained using pattern projection techniques with stereo vision systems involving periodic 2D patterns or pseudo-random 2D patterns for dynamic triangulation.

In urban/rural semantic segmentation, [10] propose a DL approach using RGB-D images extracted from traffic scenes. They adapt AlexNet for semantic pixel-wise segmentation, improving accuracy on contrast maps.

[21] use a DL brain network for semantic segmentation in commercial buildings. Their dataset covers 13 building components, employing DeepLab for segmentation and validating its effectiveness against other DL techniques.

RGB-D images are also utilized in localization tasks and 3D object part segmentation, showcasing their true potential in diverse computer vision applications [22].

3.2 INFRARED CAMERAS

Thermography, also known as thermovision, is a secure and precise system that provides real-time infrared imagery depicting the surface temperature of objects. These images are commonly portrayed using false color scales, wherein each color represents a distinct temperature range. When coupled with AI-powered image processing, Infrared Thermography (IRT) demonstrates remarkable proficiency in identifying and scrutinizing instances of damage or failure [12].

Table 1 presents a comprehensive overview of research studies on defect detection and classification using various ML and DL approaches applied to thermal and infrared images. These studies address critical challenges in diverse domains, from industrial equipment monitoring to photovoltaic (PV) module inspection. Researchers have explored novel approaches and algorithms to accurately identify defects, faults, and anomalies in different objects and components, leveraging the power of AI [12].

Table 1. Advancements in Defect Detection Using Thermal and Infrared Imaging: A Comparative Review of DL and DL Approaches

Researchers	Research Idea	Problem to Solve	Methodology	Results	Main Contribution
[23]	MLP for thermal condition classification	Classify thermal conditions into “defect” and “non-defect.”	Extract statistical features and augment with a graph cut.	Improved classification performance	Effective use of MLP and graph cut for defect detection
[24]	CNN for fault detection in cooling radiators	Detect faults in cooling radiators.	VGG-16-based CNN architecture	High performance and accuracy in various conditions	Effective application of CNN for fault detection
[25]	DL model for temperature increase detection	Detect temperature increases in high-voltage instruments.	Infrared thermal image-based CNN followed by ML models	Effective classification of defective and non-defective classes	A novel model for temperature increase detection
[26]	ANN for fault classification in electrical equipment	Classify faults in electrical equipment.	Use of coefficient features	Improved performance compared to raw data	Better fault classification using coefficients
[27]	Deep Neural Network for infrared image classification	Classify infrared images into “defect” and “non-defect.”	Opposition-based Dragonfly Algorithm for feature extraction	Outperforms other methods in classification performance	Improved infrared image classification
[28]	DL algorithms for defect detection in PV modules	Detect defects in infrared images of PV modules.	VGG-UNet and Mask R-CNN architectures	Successful automatic identification of defects in PV modules	Application of DL algorithms for defect detection in PV modules
[15]	DL algorithms for defect detection in PV modules	Detect defects in infrared images of PV modules.	VGG-UNet and Mask R-CNN architectures	Successful automatic identification of defects in PV modules	Application of DL algorithms for defect detection in PV modules
[29]	DL algorithms for defect detection in PV modules	Detect defects in infrared images of PV modules.	VGG-UNet and Mask R-CNN architectures	Successful automatic identification of defects in PV modules	Application of DL algorithms for defect detection in PV modules

Each row in the table represents a distinct research effort and highlights the key components of the study, including the authors’ names, the research idea, the specific problem they aim to solve, the methodology adopted, the achieved results, and the main contributions of their work. By summarizing these essential aspects, the table allows readers to quickly grasp the core aspects of each study and comprehend the advancements made in the field of defect detection using thermal and infrared imaging techniques [6].

The selected research works demonstrate a variety of methodologies, from traditional approaches such as Multilayer Perceptrons (MLP) and Artificial Neural Networks (ANN) to cutting-edge techniques such as Convolutional Neural Networks (CNN) and DL architectures such as VGG-UNet and Mask R-CNN. Utilizing different algorithms and models signifies the ongoing efforts to optimize and enhance the accuracy and efficiency of defect detection systems [12].

3.3 DIGITAL PHOTOGRAMMETRY AND TERRESTRIAL LASER SCANNING

Photogrammetry and 3D laser scanning technologies have significantly propelled the field of geomatics, offering accurate measurements of objects' dimensions, shapes, and spatial placement. Within the geospatial realm, ML and DL methodologies have effectively found applications in tasks such as point cloud classification and semantic segmentation [30].

Table 2 provides a comprehensive overview of research studies in geomatics that utilize DL approaches to analyze and segment 3D point clouds. Geomatics involves the collection, processing, and analysis of spatial data, and DL has shown significant potential for enhancing the accuracy and efficiency of various geomatic tasks.

The researchers listed in the table have contributed novel ideas and methodologies to address specific 3D point cloud analysis challenges. Each study focuses on a unique research idea and seeks to solve specific problems, such as semantic segmentation, feature extraction, and object recognition. These DL-based approaches offer valuable insights into processing complex 3D data from diverse sources, including lidar systems and remote sensing platforms.

Table 2. DL Approaches for 3D Point Cloud Analysis in Geomatics

Researchers	Research Idea	Problem to Solve	Methodology	Results	Main Contribution
[31]	DL algorithm for 3D point cloud semantic segmentation	Direct semantic segmentation of 3D point clouds	DL architecture for semantic segmentation	Improved performance in semantic segmentation	Pioneering DL algorithm for direct 3D point cloud semantic segmentation
[32]	Optimized DL architecture for 3D point cloud segmentation	Capture local geometries in point clouds	Hierarchical grouping to enhance local feature learning	Better performance compared to other methods	Enhanced DL approach for improved 3D point cloud segmentation
[33]	DL approach for handling 3D point clouds with spectral information	Accommodate complex 3D data from Lidar systems	Modified PointNet for spectral 3D point cloud processing	Outperformed other methods	Efficient DL model for spectral 3D point cloud analysis
[34]	DL approaches for semantic parsing of urban building point clouds	Semantic parsing of 3D point clouds of urban buildings	DL-based semantic parsing techniques	Accurate semantic segmentation of urban building scenes	Extensive use of DL methods for urban building point cloud analysis
[6]	Improved DGCNN for semantically segmenting architectural 3D point clouds	Semantically segment 3D point clouds of architectural elements	Improved DGCNN with meaningful features	Efficient and accurate semantic segmentation of architectural elements	Advanced DL approach for Digital Cultural Heritage (DCH) applications
[35]	DL-based framework for road marking extraction and classification from MLS point clouds	Extraction, classification, and completion of road markings from 3D MLS point clouds	Modified UNet architecture and clustering-based approach	Accurate extraction and classification of road markings	DL-based framework for efficient road marking analysis in MLS point clouds

3.4 REMOTE SENSING: MULTISPECTRAL AND HYPERSPECTRAL DATA

In recent years, remote sensing has seen significant advancements with the integration of ML and DL approaches, particularly in the analysis of Multispectral (MSI) and Hyperspectral (HSI) images [36]. These approaches have been adopted to expedite time-consuming processes in various studies. This section focuses on papers utilizing DL algorithms for HSI/MSI image classification of urban/rural scenes [37].

Table 3 provides a comprehensive overview of several pioneering research studies that have leveraged DL methodologies for image classification in remote sensing. Each study offers unique insights into developing and applying DL-based architectures for solving specific problems in remote sensing analysis. The researchers' ideas, problems addressed, methodologies employed, results obtained, and the main contributions of each study are summarized and organized.

Table 3. Summary of DL-based Approaches in Remote Sensing for Image Classification

Researchers	Research Idea	Problem to Solve	Methodology	Results	Main Contribution
[38]	Evaluate supervised ML classifiers for vegetation classes	Discrimination of vegetation physiognomic classes	Supervised ML classifiers (Random Forests)	High accuracy and kappa coefficient	Identification of the best classifier for vegetation classification
[39]	Spectral-spatial residual network for HSI classification	Hyperspectral image classification for various scenes	Spectral-spatial residual network (SSRN)	Good classification accuracy	Effective architecture for HSI classification
[40]	Introduce various CNN architectures for HSI classification	Hyperspectral image classification with spatial context	Convolutional Neural Networks (2DCNN, 3DCNN, recurrent 2DCNN, recurrent 3DCNN)	Improved classification accuracy	Comparison of DL methods against traditional ones
[41]	Propose a semi-supervised DL approach for HSI classification	Utilize limited labeled data and pseudo-labels	A semi-supervised DL approach with unlabeled data	Enhanced classification performance	Efficient utilization of limited labeled data
[42]	Classification framework based on spectral-spatial features	Hyperspectral image classification with spectral and spatial features	Local discriminant algorithm for spectral features, CNN for spatial features	Superior classification accuracy	Effective combination of spectral and spatial features
[43]	A DL-based target detection method for hyperspectral images	Detect changes in hyperspectral images	Convolutional Neural Network (CNN)	Accurate anomaly detection	Effective DL approach for target detection
[44]	Active DL for hyperspectral image classification	Select informative training samples actively	Weighted incremental dictionary learning, active training	Improved classification performance	Efficient active learning in hyperspectral image classification
[45]	X-ModalNet framework for MSI and SAR classification	Classify multispectral and synthetic aperture radar data	Cross-modal DL framework (X-ModalNet)	Improved classification performance	Effective cross-modal DL approach for remote sensing data
[46]	Unsupervised DL for detecting changes in SAR images	Detect changes in synthetic aperture radar images	Convolutional Neural Network (CNN)	Successful change detection	Effective unsupervised DL approach for change detection

3.5 GNSS POSITIONING

GNSS (Global Navigation Satellite System) has revolutionized positioning systems, offering low-cost solutions for various applications, including trajectory forecasting. With the increasing availability of GNSS data, researchers have actively explored its applications in pedestrian and vehicle trajectory analysis. This table summarizes several significant research papers that leverage DL techniques for trajectory analysis based on GNSS data [47].

Table 4 presents a compilation of recent research studies focusing on transport mode estimation and short-term traffic prediction using GPS trajectories. GPS (Global Positioning System) has become a widely available technology, offering vast amounts of movement data for pedestrians and vehicles. As a result, trajectory forecasting has gained significant attention due to its numerous real-world applications in transportation management, traffic control, human behavior research, and more.

Table 4. **Research Studies on Transport Mode and Traffic Prediction Using GPS Trajectories**

Researchers	Research Idea	Problem to Solve	Methodology	Results	Main Contribution
[48]	Estimation of users' transport modes from movement trajectories using a deep neural network for automatic feature extraction.	Transport mode estimation from movement trajectories.	Deep neural network for automatic feature extraction in a supervised manner.	Demonstrated effectiveness through experiments using real datasets.	Proposed method for automatically extracting features using a deep neural network for transport mode estimation.
[49]	Non-parametric, data-driven methodology for short-term traffic prediction using an advanced K-Nearest Neighbor algorithm.	Short-term traffic prediction based on similar traffic patterns.	Advanced K-Nearest Neighbor algorithm with winsorization and rank exponent.	Robust methodology demonstrated through large datasets from different regions.	Presented a data-driven method for short-term traffic prediction, outperforming advanced time series models such as SARIMA and Kalman Filter.
[50]	Inferring hybrid transport modes using GPS data and tree-based ensemble models.	Identification of hybrid transport modes from GPS data.	Statistical approach for global features and tree-based ensemble models for classification.	Improved classification accuracy through the use of tree-based ensemble models.	Proposed method for identifying hybrid transport modes based on GPS data, achieving better performance than traditional methods.
[51]	Efficient travel mode identification using raw GPS data and a tailored deep neural network.	Efficient travel mode identification from raw GPS data.	Tailored deep neural network architecture for travel mode identification.	Significantly exceeded state-of-the-art travel mode identification results.	Introduced an efficient deep neural network approach for travel mode identification using raw GPS data.
[52]	SECA: Combining autoencoder and convolutional neural networks for mode classification.	Mode classification of GPS trajectories.	SECA architecture combining autoencoder and convolutional neural networks.	Addressed issues in transportation planning and management using the SECA model.	Introduced SECA architecture for model classification, overcoming the limitations of hand-built functionality in modality inference models.
[53]	Data-driven approach using GPS and sensor-based traces to understand visitor	Understanding visitor trajectories in urban parks for planning and management.	Trajectory classification algorithm for urban park usage analysis.	Provided insights into park visitor trajectories through a data-driven approach.	Introduced a data-driven method for understanding how urban parks are used by

trajectories in urban parks.	visitors, facilitating park planning and management.

4. DISCUSSION

This article offers a comprehensive exploration of the intersection between geomatics and GeoAI, highlighting the pivotal role of geomatics as a fundamental source of complex 2D or 3D spatially referenced data. It emphasizes the multidisciplinary nature of geomatics, incorporating various sub-disciplines such as surveying, geodesy, photogrammetry, and remote sensing. This paper examines the integration of AI, ML, and DL techniques in geomatics, showcasing their effectiveness in handling diverse datasets and extracting meaningful patterns.

The discussion is organized into distinct sections that cover different aspects of GeoAI. The algorithms and models for GeoAI are explored, emphasizing the transformative impact of AI and DL in handling large and intricate geospatial data. The article underscores the significance of remote sensing data gathered through satellites, aircraft, and drones as a fundamental input for AI and ML algorithms. Applications of remote sensing in environmental management, disaster response, precision agriculture, and beyond are detailed, highlighting GeoAI's potential for informed decision-making and sustainable development.

The subsequent sections delve into specific technologies, such as RGB-D cameras, infrared cameras, digital photogrammetry, terrestrial laser scanning, and GNSS positioning. Each technology is discussed in the context of its role in geomatics and its integration with AI and DL techniques. The article provides examples of how AI algorithms, particularly DL, enhance tasks such as semantic segmentation, object detection, and defect detection in various geospatial data types.

Moreover, the discussion extends to the realm of digital photogrammetry and terrestrial laser scanning, illustrating their impact on geomatics and how ML and DL methodologies enhance point cloud classification and semantic segmentation.

In remote sensing, the article explores the applications of ML and DL in analyzing multispectral and hyperspectral data. The tables summarize key research studies, showcasing the diverse methodologies employed for image classification, defect detection, and change detection in remote sensing applications.

This article concludes with a focus on GNSS positioning, elucidating how this technology has revolutionized positioning systems and trajectory forecasting. Various research studies are presented, demonstrating the application of deep neural networks for transport mode estimation and short-term traffic prediction using GPS trajectories.

5. CONCLUSIONS

AI and ML have significantly transformed various fields, including geospatial analysis. This area benefits from the inherent characteristics of data, making ML and DL approaches particularly suitable. These advanced techniques have outperformed traditional geospatial modeling, as they help overcome the complexities associated with heuristic-based simulations and model-based representations.

The paper presents a comprehensive survey of the literature on implementing AI in geomatics, with a specific focus on ML and DL techniques. The authors observe a recent increase in the use of RGB-D data but a slight decline in the utilization of IRT data compared to the previous year. Previously, IRT data had seen a surge from 2017 to 2019, but it experienced a downturn in 2020. Similarly, research on HSI/MSI data was widespread in 2016 and 2017 but declined until 2020, when renewed attention was given to the topic. On the other hand, research on IRT and PC was scarce in 2016 but has made significant progress in recent years. Due to its versatility and practicality, point cloud processing has expanded into various fields such as structural engineering, manufacturing, transportation, construction, forestry, environmental studies, and industrial engineering.

The authors underscore the significance of RGB-D images, thermal imagery, HSI (Hyperspectral Imaging), MSI (Multispectral Imaging), and the analysis and management of point clouds within the context of GeoAI. These AI techniques are pivotal in advancing infrastructure development and overall progress. Within geomatics data analysis, numerous challenges, such as point cloud alignment, semantic segmentation, object detection, and image classification, have been effectively tackled through AI methods. The paper examines the methodologies and techniques tailored to each type of geospatial data, categorizing and contrasting them from various perspectives while spotlighting their specific strengths and limitations.

Moreover, the authors furnish compelling illustrations of GeoAI applications, encompassing input formats, architectural classifications, and applied techniques. This comprehensive review enhances comprehension of research issues associated with the implementation of AI in geomatics, setting the stage for further exploration. The paper also suggests future research directions, which include augmenting algorithms by incorporating comprehensive features to enhance performance. Furthermore, it underscores the urgent need to make AI models interpretable and understandable, particularly in light of the ethical concerns posed by “black box” operations, especially within high-stakes decision-making contexts. The lack of transparency in deep neural networks makes it challenging to justify their use ethically. Hence, introducing interpretability and explainability techniques, such as visualization, becomes imperative to facilitate human analysis. Ensuring that AI techniques are interpretable, sustainable, and dependable is paramount, given the escalating demand for ethical AI solutions.

In summary, this article not only introduces the reader to the fundamental concepts of GeoAI and geomatics but also provides in-depth insights into the applications of AI and DL across various geospatial technologies. The comprehensive discussion and examples underscore the transformative potential of GeoAI in shaping the future of geospatial data analysis and decision-making.

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CONFLICTS OF INTEREST

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