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Reflections on the Application of Artificial Intelligence in Geographic Information Science Based on AI Prediction Functions

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Abstract. In recent years, with the increasing prominence of artificial intelligence topics, more and more people are investing greater efforts in AI, big data analysis, and related fields. These efforts have yielded substantial returns, as evidenced by the emergence of ChatGPT, DeepSeek, Claude, and numerous other large AI models that provide considerable convenience across various industries. Based on these developments, this paper primarily focuses on the application of intelligent AI models' prediction functions in geographic information science research. It analyzes the progression from traditional statistical models through shallow machine learning to deep learning, explores the current integration of artificial intelligence with geographic information science, and further examines the positive outcomes and applications generated by combining AI with specific domains related to geographic information science. Additionally, it summarizes the current deficiencies in geographic artificial intelligence and its developmental trends.

Keywords: Geographic Information Science; Artificial Intelligence; Machine Learning; Deep Learning.

1. Introduction

Decades ago, researchers in computer science foresaw that the accumulation of massive amounts of data would bring both opportunities and challenges to computer science and other fields. In 1995, Academician Li Deren pioneered the advocacy for knowledge discovery from GIS databases [1]. Subsequently, Harvey and colleagues proposed an academic journal that showed the intersection of big data technology with the field of geography.[2] In recent years, with the rise of artificial intelligence technology, an increasing number of AI models have been applied across various domains, particularly in predicting developmental trends. Examples include using AI to predict cancer-driving mutations in the medical field [3], predicting autonomous vehicle trajectories in transportation [4], and forecasting weather conditions in geographic information systems [5].

Climate prediction has long been a challenge in the field of geographic information science. Extreme weather and climate events, such as heatwaves, droughts, floods, and storms, occur frequently, severely affecting regional economies, industrial and agricultural development, and the lives and property of people. To better respond to meteorological disasters and environmental changes, humanity has consistently sought to understand and predict the evolution of the natural environment.

Geospatial intelligent prediction, a technology that predicts future attributes or state values based on the historical high-dimensional attributes of spatial objects [6], represents a typical case of deep integration between geographic information science and artificial intelligence. Research projects combining artificial intelligence with geographic information science, such as geospatial intelligent prediction, have become frontier topics in geospatial artificial intelligence [7]. These studies have completed tasks in many important fields that were previously unachievable.

2. Development Status of Geographic Information Science and AI Prediction

2.1 AI Prediction Based on Statistical Mathematical Principles

Spatial intelligent prediction based on statistical learning can be divided into two categories: prediction based on classical statistics and intelligent prediction based on shallow machine learning.

It is worth noting that shallow machine learning also relies on probability theory and statistical inference, making it essentially an extension of statistical learning [8].

2.1.1 AI Prediction Based on Classical Statistics

Prediction based on classical statistics is an early prediction technology that aims to predict unknown attribute information of geospatial objects by establishing specific parametric models [9]. These methods can be roughly divided into three categories: prediction methods that consider only spatial dependence, prediction methods that consider only temporal dependence, and prediction methods that combine both spatial and temporal dependence. For example, the Thornthwaite equation, proposed by climatologist C.W. Thornthwaite in 1948, estimates potential evapotranspiration (PET) based on temperature and precipitation data, representing a prediction method considering only temporal dependence. In contrast, kriging interpolation and nearest neighbor interpolation are mathematical analysis methods that consider spatial dependence. Combining both approaches yields comprehensive calculations considering both temporal and spatial data, such as spatiotemporal kriging interpolation.

These statistical models typically have explicit mathematical expressions and possess certain advantages in computational efficiency and generalization. However, they also face problems of low prediction accuracy and limited universality. Fundamentally, traditional statistical models strictly adhere to mathematical formulas, whereas real-world scenarios often fail to meet the preset conditions of these models. Even when models meet requirements, the data needed for prediction may not be easily obtainable. Furthermore, traditional statistical learning models are parametric models, which struggle to effectively capture the complex, nonlinear spatiotemporal relationships embedded in the states of geographic elements [10].

2.1.2 AI Prediction Based on Simple Machine Learning

With the development of big data technology, the increasing volume of data has provided fertile ground for data-driven simple machine learning. Support vector machines, random forests, and convolutional neural networks are often employed in various prediction tasks due to their high computational efficiency and ability to reveal nonlinear relationships, as well as their ability to display feature vectors. However, in geographic-related intelligent prediction tasks, classical simple machine models often perform poorly. The reason is that geospatial data exhibits complex spatial autocorrelation and temporal dependence. Still, the independent and identically distributed assumption of classical shallow machine learning models contradicts this characteristic, thereby limiting their effectiveness in geospatial intelligent prediction. Moreover, while AI models can passively explain spatial heterogeneity characteristics reflected in magnitude differences or fluctuations in geographic data, they lack theoretical descriptions and comprehensive cognition of the heterogeneity characteristics of spatial variables or their relationships [11]. To address this issue, many researchers have developed targeted extensions to ordinary learning models, enabling machine learning to meet the demands of geographic data prediction.

For instance, regarding spatial dependence, artificial intelligence has made remarkable achievements in urban planning. In the past, urban planning and construction data were often displayed on large physical maps with information integrated on tracing paper. Subsequently, the birth of Geographic Information Systems (GIS) transformed the paper-based information analysis method. In the 1970s, artificial intelligence began being applied in the geographic field. Entering the 21st century, governments worldwide are beginning to address problems brought by urbanization. Sustainable urban development and harmonious coexistence with nature increasingly depend on the successful planning of urban expansion and regional geographic planning and design [12]. As research breadth and depth increase, artificial intelligence plays an efficient and reliable role by transforming complex qualitative descriptions in space into quantitative analysis and design models. This is primarily reflected in the use of the Non-dominated Sorting Genetic Algorithm III and ensemble learning algorithms to advance TOD (Transit-Oriented Development) planning, demonstrating superiority in passenger volume objectives with better convergence effects compared to linear models. Golej et al. [13] combined Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Principal Component Analysis (PCA) with high-resolution satellite imagery for vehicle detection [14].

Another article primarily focuses on the analysis and prediction of PET (potential evapotranspiration) with temporal dependence. The article proposes that PET is one of the important indicators for studying moisture loss in geographic hydrological systems; however, due to a lack of comprehensive data, accurately calculating PET remains a challenge today. Therefore, researchers proposed a detailed model using the Thornthwaite equation to predict sustainable PET, which requires only the monthly average temperature and latitude. Combined with machine learning support vector machines and random forests, relying on meteorological data provided by GIS, and establishing a Python database to drive intelligent models while strictly adhering to model and uncertainty analysis to compensate for data insufficiency, this model ultimately performed significantly better than other traditional models [15].

2.2 AI Prediction Based on Deep Learning

Deep learning is a branch of machine learning that integrates the advantages of supervised learning, unsupervised learning, and reinforcement learning. With revolutionary breakthroughs in computational architecture and parallel capabilities, deep learning models demonstrate unprecedented accuracy and potential for broad cross-domain applications [16]. Compared to classical statistics and shallow artificial intelligence, deep learning models have better capabilities for capturing complex nonlinear relationships and automatic feature learning patterns while avoiding the defects of single-direction AI models (supervised learning requires large amounts of labeled datasets, unsupervised learning results have strong subjectivity, and reinforcement learning has limitations in balancing exploration of new possibilities and known strategies).

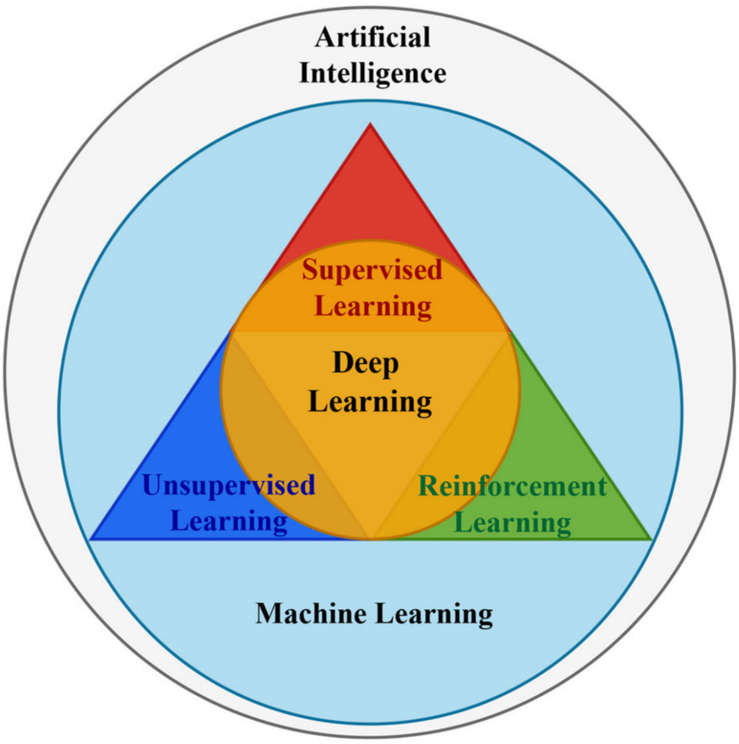

Figure 1. Hierarchy of AI methods and learning paradigms.[17]

In nonlinear, large-volume data analysis with ambiguous objectives, deep learning models demonstrate advantages. Currently, there are five mainstream geographic deep learning frameworks, divided into three major categories: spatial models with three spatial tasks—classification, detection, and segmentation; temporal models with temporal tasks—sequence frameworks; and hybrid models that combine temporal and spatial tasks [17].

For example, using hybrid ensemble-based deep learning methods to generate three-dimensional geographic models and assist uncertainty analysis, this deep learning method utilizes Dynamic Neural Network Layers (DNLNs). This technique can automatically scan data and search for composable features, even when objectives are unclear, thereby processing unstructured data and possessing greater capability in feature engineering than machine learning, which significantly reduces computation time [18].

3. Integration Applications of Other AI Functions with Geographic Information Science

Today, artificial intelligence has achieved numerous milestones by combining knowledge from various fields. Besides the prediction functions mentioned earlier, AI's analytical, classification, and generation functions also play important roles in geographic information science research. For instance, in Location Based Services (LBS) supported by geographic information system platforms, recent years have seen the integration of original cloud computing with artificial intelligence, utilizing AI encryption methods, particularly addressing the issue of sensitive user security access when sharing LBS services, proposing a new cloud-based General Spatiotemporal Role-Based Access Control model (GSTRBAC) that provides a detailed method for LBS data security based on user credentials, authorized locations, and access times [19]. Additionally, in remote sensing geography, another hot topic combining with artificial intelligence, a new AI model called LuoJiaAI, based on cloud technology, has emerged on remote sensing image interpretation platforms. This AI platform consists of a standard large-scale sample database and an AI framework capable of deep learning (LuoJiaNET), achieving state-of-the-art performance in five classic remote sensing interpretation tasks: scene classification, object detection, land use classification, change detection, and multi-view 3D reconstruction [20]. In the field of remote sensing and geographic data processing, although machine learning and deep learning have tremendous potential in modeling various remote sensing tasks, differences in geographic data collection methods and spatial metadata processing approaches make deep learning applications extremely challenging. Addressing this point, some have applied artificial intelligence to handle data compatibility issues. For example, the geographic AI model TorchGeo is a Python library that integrates geospatial datasets into the PyTorch deep learning ecosystem, assisting in classifying unclassified, composable data and facilitating the compatible transformation of multispectral data [21].

4. Challenges Facing Geographic Artificial Intelligence and Future Development Trends

Although the combination of artificial intelligence with geographic information science and other geographic fields has great development potential, numerous challenges and deficiencies remain, awaiting future optimization and iteration. A paper from the School of Geodesy and Geomatics at Wuhan University mentions that machine learning (ML) has historically played a significant role in environmental remote sensing monitoring research. However, with the continuously increasing volume of "big data" obtained from Earth observation, more innovative methods have emerged to assist Earth remote sensing observations. Over the past decade, deep learning frameworks born from machine learning foundations have demonstrated stronger performance. In the future, combining physical models with deep learning models must also incorporate geographic laws into learning frameworks. Besides model optimization, the article also mentions that geographic model learning has the deficiency of requiring large amounts of data and time [22]. Currently, large geospatial intelligent models have massive parameters numbering in the hundreds of millions, comprising numerous convolutional layers that capture spatiotemporal dependencies over extensive ranges. Excessive neural network layers can cause difficulties in deploying models in application scenarios, and deeper network structures exacerbate the risk of over-smoothing and overfitting in spatially intelligent prediction models, thereby damaging model performance and increasing model complexity [23]. In another area of remote sensing, remote sensing image interpretation involves a wide range of knowledge types, and interpretation applications combine various types of knowledge with data to produce meaningful results. However, these applications are mostly limited to point solutions of specific knowledge on particular problems, lacking systematicity and comprehensiveness, with models operating in various directions independently without being well-integrated [24]. Although the integration of geographic information systems with artificial intelligence into geographic intelligent agents is an inevitable trend, these agents still face numerous challenges when addressing complex geographic problems, particularly in terms of interacting with the real world and independently completing entire sets of geoscience task flows. Existing system architectures still need further improvement to adapt to more complex decision-making requirements [25]. Although research on small geographic intelligent models is becoming increasingly in-depth, research on the mechanisms and basic theoretical research for generating large geospatial models is relatively scarce, and there is also a lack of research on the relationship between geospatial digital twins and geospatial digital intelligence [26].

5. Conclusion

Taking predictive functionality as the starting point, this paper reviews and explores the developmental history, integrated applications, and future trends and challenges of artificial intelligence in the field of Geographic Information Science. It points out that since the initial integration of artificial intelligence and geographic information science, following developments based on classical statistics and simple machine learning, the current research mainstream has shifted to deep learning models, which have addressed key shortcomings of their predecessors. By examining applications of current GeoAI models, the paper elaborates on the opportunities and challenges encountered in the development of artificial intelligence. It concludes that while the integration of artificial intelligence and Geographic Information Science holds significant potential, the inherent complexity and diversity of geographic data mean that the development of their synergy still has a long way to go.

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