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REVIEW

Geospatial Artificial Intelligence (GeoAI): Applications in Health Care

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Abstract

GeoAI is a new emerging research area that refers to set of technologies that integrate AI technology with a diversity of GIS (Geographic Information System) techniques. The present study observed that GeoAI goes beyond current GIS expectations and into the domain of possibility in the not-too-distant future. This emerging interdisciplinary science will lead us to sustainable decisions and explore the most suitable solutions to the existing problems. GeoAI has the potential to transform current geography and geomatics programs by incorporating a GeoAI dimension into modern GIS curricula. In this review, we have studied the application GeoAI in various healthcare fields. GeoAI has the potential to revolutionize healthcare, public health, infectious disease control, disaster aid, and the achievements of Sustainable Development Goals (SDG). in healthcare, GeoAI can help with disease diagnosis, treatment planning, and resource allocation. In public health, it can aid in disease surveillance, emergency response planning, and identifying health disparities. In infectious disease control, GeoAI can help predict and track disease outbreaks and support vaccination campaigns. In disaster aid, GeoAI can provide real-time data on environmental hazards and their impact on public health. In achieving Sustainable Development Goals, it can support in land use planning, urban development, and resource allocation to promote health and environmental sustainability. Overall GeoAI has the potential to transform multiple sectors and improve the wellbeing of populations worldwide.

Keywords: Geographic information system, Artificial intelligence, GeoAI, Health GIS

1. Introduction

GIS (Geographic Information System) technology is one of the valuable information systems for creating accurate mapping areas and locations so that people may acquire information more easily. GIS examines and illustrates location-related issues in geospatial research, natural resource management and environmental science issues by combining various spatial data with numerous attribute data and generating information utilizing diverse tools and modelling techniques of spatial analysis [1]. GIS technology has existed for over 50 years, with the introduction of the initially well-known GIS application, Canadian Geographic Information System. During this time, GIS has progressed from a niche technology to one with widespread application and has significance across a variety of fields [2]. With breakthroughs in artificial intelligence (AI), the use of AI in a variety of sectors is growing, and now Geospatial Artificial Intelligence (GeoAI) is gaining

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importance as a new area of combining spatial science with AI to aid in the visualization of patterns and bring insight [3].

For a long time, the AI group has been seeking to replicate intelligent behavior of humans with computer programmers. This is a difficult task, because computer software must be capable of completing a wide range of activities to be deemed clever. Fig. 1 shows the components of AI.

There are numerous meanings available for AI, but the majority of them fall into one of two categories.

- System which thinks and acts Like human
- System which thinks and acts Rationally

GeoAI is a new emerging research area that refers to a set of technologies that integrate AI technology with a diversity of GIS techniques, like spatial data processing, Spatial big data analysis, Geo-DBMS (Data Base Management System), as well as the analysis and synthesis of algorithms (GeoAI), this includes all terms that refer to a collection of technologies that allow AI and GIS to work together. In the last few years, AI in GIS has steadily been the primary interest of geoscience research and application [3]. Components of GeoAI can be seen in Fig. 2.

GIS, remote sensing, and satellite technology aid all Geospatial visualization, analysis, design, control, and decision-making. Because of its geo-intelligence, GIS distinguishes out among other information systems. The four layers of this system are geo-visualization, G-DSS (Geo-Decision Support System), geographic design, and geo-control [4].

GeoAI technology comprises of following parts.

- **GeoAI:** A product of AI and GIS combines spatial data processing, analysis, and algorithm building.
- **Artificial Intelligence for GIS**: Using AI capabilities to improve GIS software's functionalities and user experience.
- **GIS for AI:**Perform spatial visualization and additional geographic analysis of AI output data using GIS visualization and analysis technologies [2,4].

2. GeoAI and GeoAI technologies

DL (Deep learning) is a popular study topic and a subset of ML (machine learning), which lies at the heart of AI. The two aspects of GeoAI are spatial machine learning and spatial deep learning. Using Super map as an instance, users could employ geospatial machine learning to find a solution to a variety of GIS application difficulties, including geographic clustering, spatial regression and spatial classification. Geospatial deep learning can accurately distinguish time and space elements in geospatial data. As well as instinctively and effectively building heterogeneous features, resulting in data-driven earth science studies. Geospatial Deep Learning methods incorporate 3D data with picture assessment, as well as neural network analysis [5].

Figs. 3 and 4 shows the integration of Machine Learning and Deep learning operators in GeoAI respectively. The spatial properties of ground objects vary by region and season, a GeoAI algorithm process resource should be included to allow the

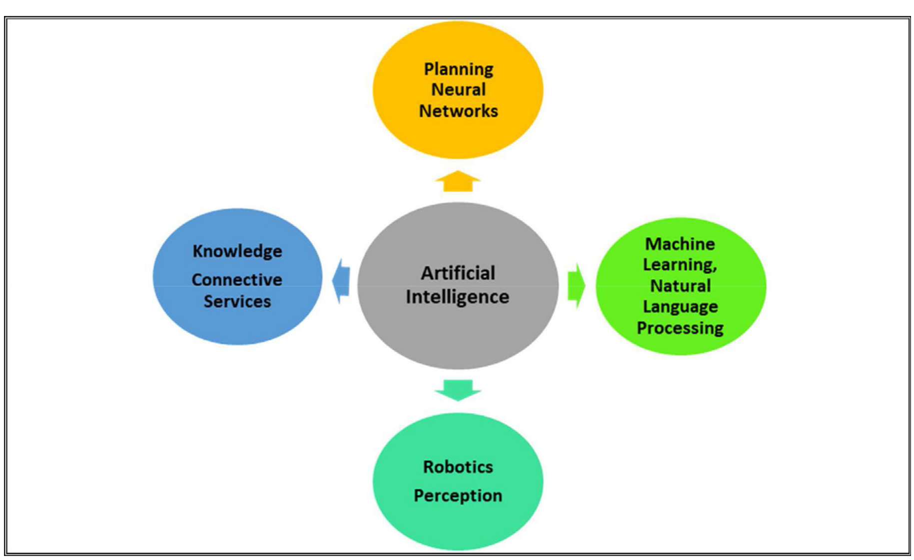

Fig. 1. Components of Artificial Intelligence.

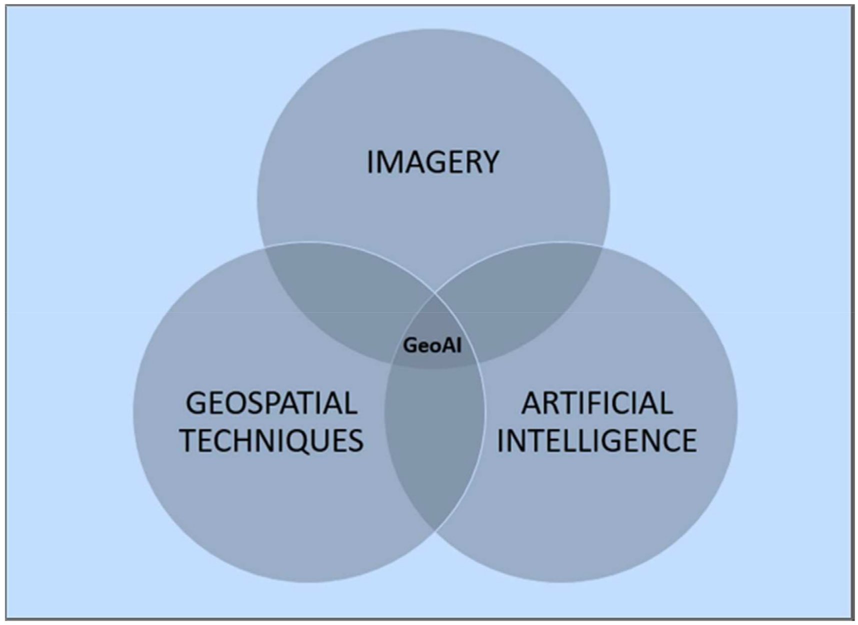

Fig. 2. Components of GeoAI.

implementation unit to continue to keep the model based on its own set of data attributes, improving model rationale achievements rates as well as dependability [6]. Workflow of GeoAI is given Fig. 5.

The important question now is, "How has GeoAI evolved over time?" Consider a four-generation progression of GeoAI advances, each marked via reformations to following 7 main dependent drivers, namely: Hardware technologies, access and availability of data, level of connectivity, machine learning technologies, software technologies, GIS roles and output [5,6].

Deep learning and machine learning can use geospatial data as a vast dataset to increase the accuracy of their analysis. Because 80 percent of the datasets we produce today are geospatial, GeoAI inherently has applicability in other core industries. There is something for everyone, whether it is agriculture, driverless vehicles, climate change, or security. GeoAI finds a wide range of applications in all of these domains because the data collected is mostly geographical in nature [5].

Geospatial technologies that create accurate data with 3D information include LiDAR, satellite imaging, drone mapping, and surveying ground cameras. When considerations such as enormous data volume and other criteria are taken into account, it becomes practically impossible for the human mind to arrive at the most conclusive or lowest risk scenario. AI incorporated in spatial technology can aid with this by assisting in the analysis of numerous variables, which the AI can then analyze in real-time

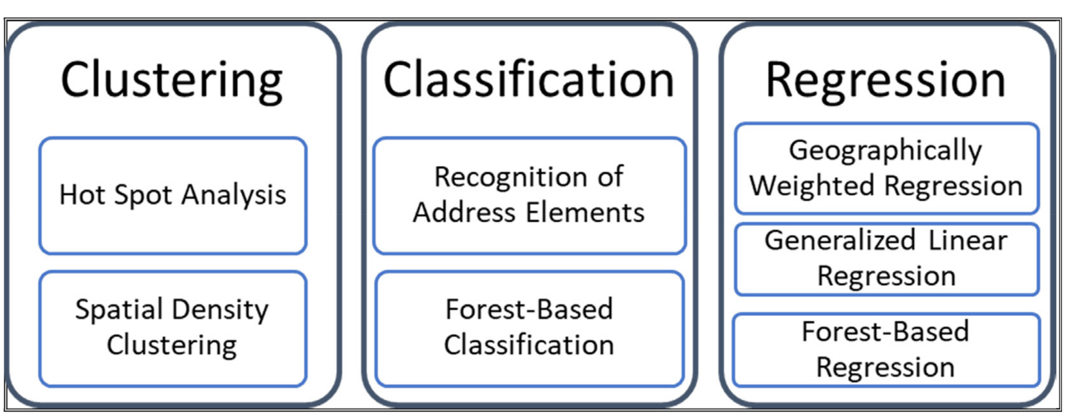

Fig. 3. Geospatial machine learning operators.

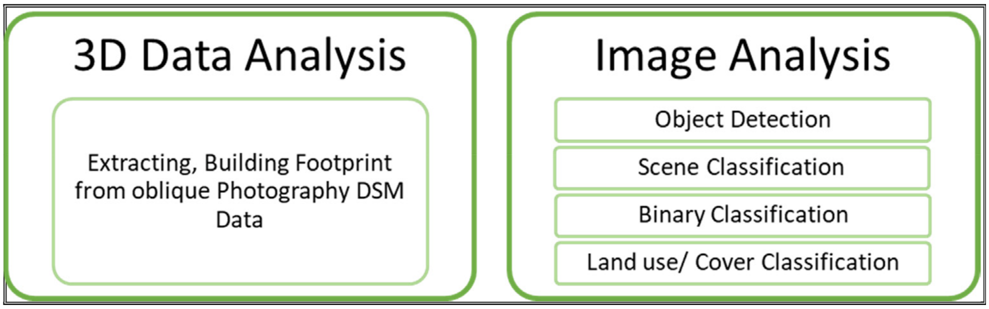

Fig. 4. Geospatial deep learning operators.

utilizing realistic 3D data with an almost-human perspective. Consider GeoAI in self-driving cars, which can tackle complicated problems in congested regions without the need for human intervention and without making mistakes [5,6].

A number of coupled causes have propelled the recent emergence of GeoAI as a field that is currently garnering a lot of interest. These are some of the motivators.

- The enhancement of computing & graphics hardware (i.e., robust CPUs & GPUs, and recently TPUs).
- Since the early 2010s, there has been greater distribution and access to cluster cloud computing (e.g., AWS, Azure, NVIDIA); breakthroughs in Deep Learning (DL) methods and applications.
- Enhancement and flexibility of GIS software (for example, ArcMap to ArcGIS Pro + ArcGIS Enterprise/ArcGIS Online).
- More material on machine learning and deep learning algorithms (e.g., Tensor Flow, Pyro).
- The exponential growth in data gathering and accessibility (80% of all data is geo-tagged), as well as cheaper and larger database storage [6].

Most current AI classifiers along with models employed in practical mapping mostly utilize single date spectral data for classifications due attributable to technological constraints of utilizing abundant time series data for defining land cover fluctuations [7]. DL has recently showcased remarkable outcomes in a variety of disciplines, including remote sensing. Because of their ability to gather feature representations solely out of primary data devoid of necessity for domain specific knowledge [2,3], DNN [Deep Neural Networks] have been employed in assignments such as semantic segmentation, object detection, image classification, classification from mostly time series, and detection of abnormality in images from remote sensing. This budding convergence of GIS with AI is depicted as GeoAI in published work and in industries [8].

AI, such as machine learning approaches, is becoming more frequently used in health and healthcare, especially as high-performance and cloud computing technologies become more accessible [5,6]. Health intelligence is the implementation of artificial intelligence as well as data science tools and techniques for delivering trustworthy, effective, as well as dynamic perceptions in health and medical management.

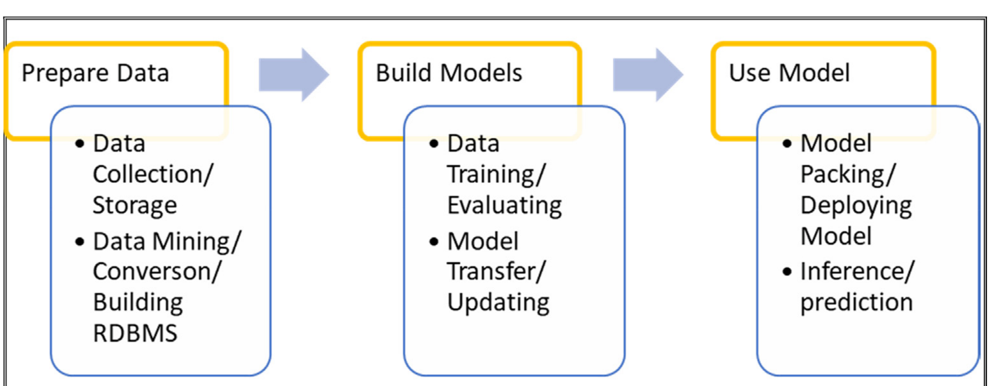

Fig. 5. Model of GeoAI flow.

3. Applications in healthcare

Artificial intelligence includes social network investigation towards syndromic surveillance predictive modelling to define groups with high disease risk [5], mobile health aimed at healthcare delivery medical imaging interpretation and much more [8].

Understanding, evaluating, and visualizing real-world occurrences based on their location is possible today because of spatial science [6]. Geospatial artificial intelligence (GeoAI) fuses methodologies from spatial science, high-performance computing, data mining and AI to generate meaningful insight out of spatial big data [6]. GeoAI is subset of health intelligence which uses geography in order to provide functional data which may be utilized for human health improvement. Various innovative origins like EHR, Satellite remote sensing, social media and personal sensors for spatial big data can be utilized to enhance the field of public health science (particularly in 'smart healthy cities' perspective) along with presumably precision medicine, crafting novel possibilities to further thoroughly respond to queries routinely sought in these fields along with unique queries, is a prevailing concept throughout GeoAI implementations at the individual and population level [9,10,11].

Experts may visualize, comprehend, and analyze real-world occurrences in relation to specific locations using geospatial science tools and technology (which range from sensors that record location data to GIS or Location Intelligence Systems). With the intension of examining their possible participation in altering health outcomes [12].

3.1. GeoAI in public health

Geographic analysis can be regarded as an important method capable of effectively examining troublesome hotspots of public health issues and related geographic risk indicators to help pinpoint unsafe areas where incidence of any particular disease is highest or to study the public health status. As an outcome, the efficacy of community-based efforts aimed at promoting public health. Increased understanding of the role of the potential risk areas mentioned in the preceding section may also be forthcoming. Traditional spatial analytic methodologies, on the other hand, are mostly retrospective in nature, relying on past data, which limits their prediction capacities. One method to overcome this constraint is to apply Geographical analysis aided by artificial intelligence, which allows for a powerful, predictive framework based on a variety of geotagged and time-stamped data [13].

According to Louis Sanz, CEO of CARTO *"For public health surveillance, innovative statistical approaches and computer tools, such as spatiotemporal models for disease risk prediction, cluster detection, and disease spread due to travel, can be used. This study could aid in the development of strategic policies in the fight against disease."*

Location analytics can help model behaviors and make better decisions. According to Dr Este Geraghty *"We can improve our understanding of viral transmission, determine if public health recommendations are being followed, and predict whether travel bans and other measures will quell the spread of disease using everything from maps that analyze the virus's genetic profile as it spreads from place to place to AI techniques that make sense of human movement data."*

Benjamin George et al. in their work Geospatial Artificial Intelligence Infused into a Smartphone Drone Application for Implementing Seek and Destroy in Gulu region of Uganda developed a real time, deep learning, convolution neural network [CNN], spectral signature AI models which were integrated with ArcGIS Pro version to implementing real time, sentinel site, object detection algorithms in the smartphone app for seasonal, geo referenceable, Land use Land Cover [LULC] mapping specific, Anopheles, larval habitat, capture point, attribute features, they did so to optimize the seasonal, UAV sensed, sentinel site, RGB signature, image classification of the unknown, seasonal district-level Anopheles, larval habitat, breeding site, and aquatic foci in the dashboard, which is a configurable and interactive IOS Application for implementing district-level real-time control strategies to seek and destroy the breeding sites of anopheles. Their approach is based on the Region-Based Convolution neural network (R−CNN) embedded in a mobile app. R−CNN algorithms are the family of Machine Learning models for computer vision and specifically for object detection they succeeded in merging of regional proposal network (RPN) and Fast R−CNN (it's a ML Classifier) with a dashboard environment, smartphone, interactive app to build on archived, datasets of real-time UAV sensed, Georeferenced, capture points, seasonal, aquatic, Anopheles, larval habitat, RGB sentinel site, spectral signatures by classifying grid stratifiable Land use Land Cover capture points (edges of streams and water puddles on drying streambeds, agro pastureland ecosystem, community tap foci etc.) in the study they used ArcGIS API for Python, R-ArcGIS Bridge integration to solve complex problems combining powerful built-in tools with any machine learning package required from scikit-learn and tensor flow in Python to caret in R to IBM Watson and Microsoft AI with help of all these they achieved to develop app to forecast breeding site of anopheles and destroy the anopheles and larval habitats [14].

3.2. GeoAI for epidemiological studies

In epidemiology, GeoAI has been applied to define as well as analyze disease spatial dispersion, as well as investigate the influence of location-based variables on illness outcomes. In epidemiological investigations, spatial analysis may be a highly helpful approach and can direct further research on suspected environmental causes of a disease [15]. Employing National Center for Health Statistics Natality Files, K-means Clustering (ML method) was utilized in examining spatiotemporal trends of age during gestational period in over 3000 US countries with a total of 145 million births from 1971 to 2008 to encourage generation of hypothesis associated with the etiology of preterm births [15] In effort to accurately comprehend factors of HIV prevalence, researchers of Africa employed Support Vector Regression (ML method) to generate mobility along with communication statistics from the data that was collected from mobile phones and then georeferenced [12]. The study authors observed that characteristics including the phone user's spatial region covered and total migrations were associated to HIV prevalence when these retrieved attributes were correlated to department level prevalence rates of HIV [16]. Geographic clusters of ALS have been recorded in the literature, and some of them are thought to be brought on by interaction with the environment [15]. In France, where Preun et al.'s previously published data from 2000 suggested a nationwide incidence rate of 5 cases per 100,000 people, nine instances of conjugal ALS were reported [17]. The results of the research [15] point to an overabundance of ALS patients in particular South East Asian postcode districts. An early geographical epidemiological study for the COVID-19 epidemic in Mexico was conducted [18]. They assessed the regional pattern of mortality risk among COVID-19 tested people (MRt) and went on to study the relationship between spatial predictors of MRt in various Mexican states. In two endemic villages in Kenya's Baringo district, researchers [19] looked at the spatial clustering and epidemiological aspects of visceral leishmaniosis and discovered a significant correlation between seropositivity and house construction, age, and proximity to domestic animal enclosures. They also discovered that the two villages had different patterns of spatial clustering of cases depending on risk factors [20]. investigated a variety of spatial techniques that can be used in epidemiological studies and discovered that spatial clustering techniques are the most popular method for evaluating non-random spatial structures. These techniques include Mantel bailor's test [21], Diggle and Chetcoynd's bivariate [22], potthoff-whittinghill method [23,24,25].

3.3. GeoAI for environmental epidemiology

The employment of AI technologies to uncover information from spatial data is a current hot topic that has been seen in other communities of science, such as the International Symposium on Spatial and Temporal Databases. These innovative GeoAI algorithms can be used to a variety of human health-related issues, such as environmental epidemiology [26]. Environmental exposure modeling, often utilized to undertake assessment of exposure in these studies, is one area where GeoAI technologies are starting to be applied [27]. Finally, one of the over-achieved objectives of incorporating GeoAI with environmental epidemiology is to carry out more accurate and detailed modelling of environmental exposures (than traditional strategies), which would direct to further assessment of environmental elements more accurately, to which we are exposed, and thus gain better knowledge of the possible connections between environmental factors and human health. Furthermore, GeoAI provides ways for measuring previously difficult-to-capture new exposures.

Researchers can start to make a connection about how GeoAI technologies could be especially used in environmental epidemiology, based on current research achievements and capabilities. Environmental epidemiologists use direct means to assess exposure, such as biomonitoring (e.g., measured in urine), and indirect methods, such as exposure modeling, to determine the elements to which humans may be subjected and hence may influence health. Exposure modeling entails creating a model to describe a certain environmental variable utilizing numerous data inputs and statistical methodologies [28]. When opposed to using direct approaches, exposure modeling is a more cost-effective way to examine the distribution of exposures in vast study groups [29]. Basic proximity-based metrics are included in exposure models to sophisticated modelling techniques such as kriging [30,31]. Over the last two decades, spatial science has been crucial in epidemiologic exposure modeling, allowing environmental epidemiologists utilize GIS technologies to generate and establish a relationship between exposure models and health outcomes data utilizing geographic variables to evaluate the effects of factors like the impact of air pollution on the development of cardiovascular disease [29,30,32].

3.4. GeoAI for environmental health

Global concerns such as sustainability, climate variability, and biodiversity loss are progressively being addressed with new technologies and data resources. Owing to the overlap of Artificial Intelligence and Geospatial science (GeoAI), the publicly accessible open Earth Observation data gathered via multiple satellite constellations and sensors with high spatial, temporal and spectral resolutions may now be employed for analysis of the above-mentioned concerns [33].

GeoAI has been utilized in the domain of environmental health to model environmental exposures with significant accuracy and precision [6], including determining risks that were previously difficult to quantify. GeoAI technologies are also being employed to record components of the built environment [34], for instance natural environments or urban green space. In a research intended to acknowledge the lack of map-making in developing nations for emergency aid and economic reform, CNNs (DL method) were utilized to computerize the generation of construction maps in Nigeria [35]. In complement to satellite remote sensing, mobile air quality sensors provide a unique source of geographic big data which was utilized to enhance air pollution exposure models [36]. Urban governance is a challenging task to sustain a healthy urban environment because the majority of urban settlements are characterized by shortfalls in stock housing and supply of water, urban infringements in periphery, inferior sewage, traffic jams, pollution, poverty, and social unrest. Policymakers must include remote sensing into urban planning and management because the dynamic nature of urban environments needs both macro and micro level study [37]. Unprecedented environmental changes are taking place over the planet, and they may be contributing to climatic calamities like drought and excessive heat. Dyosi [38] sought to investigate remote sensing data to evaluate and record instances of drought in Amathole district municipality (ADM) from 2007 to 2017. In order to determine the past and future urban growth paradigm and its impact on various LULC classes, the study by Tripathy [39] integrated geospatial techniques and cellular automata. It also included spatiotemporal land use land cover monitoring and urban growth modelling of Delhi, India. The most of cities and municipalities throughout the world struggle with the challenge of disposing of their urban solid waste. Accelerated population expansion, urbanization, industrialization, and rural-to-urban movement have all contributed to a severe problem with solid waste management that has an impact on the health of individuals who live in those specific areas. Thus, there is a requirement for appropriate solid waste disposal facilities. The goal of the study by [40] was to identify the most appropriate waste disposal sites for Pune Municipal Corporation using a Geoinformatics technique. Future research might apply these approaches to a bigger study region and include more time points to provide a better characterization of the built environment with high spatiotemporal resolution.

3.5. Geo AI in analysis of infectious disease

More plain and intelligible visualization, real-time tracking of validated as well as documented case numbers, contact tracing, escalation trajectory, along with identifying hotspots in order to prevent dispersion and community spread are some of the advantages of GeoAI. According to a recent analysis, 1/4th of the research included maps developed utilizing GIS techniques, particularly infectious disease mapping [41-44].

Ahasan, reviewed GIS applications and Geo-Spatial analysis in studying COVID-19. They combined big data applications, social media data mining, and geospatial contact tracing. They looked at how GIS and spatial analysis approaches had been applied in previous COVID-19 investigations. The bulk of the studies used GIS to illustrate the geographical distribution and pattern of COVID-19 transmission, Cluster analysis to detect case accumulation, outbreaks were located using hotspot analysis and access to primary health care facilities were evaluated using proximity analysis. With the passage of time, however, studies are focused on different models to forecast or simulate various features of COVID-19 utilizing geospatial methodologies were published. Different study on this issue used the spatial data panel model, Agent based model, MGWR, GWR, GIS based Maxent model and ANN were all employed in different research on this topic [45-49].

Sofiane Atek et al. (2022) conducted study on "A Geospatial Artificial Intelligence and satellite-based earth observation cognitive system in response to COVID-19". The pandemic emergency caused by the spread of COVID-19 has stressed the importance of promptly identifying new epidemic clusters and patterns, to ensure the implementation of local risk containment measures and provide the needed healthcare to the population. In this framework, artificial intelligence, GIS, geospatial analysis and space assets can play a crucial role. Social media analytics can be used to trigger Earth Observation (EO) satellite acquisitions over potential new areas of human aggregation. In their paper, an end-to-end solution has been presented, that is capable of developing efficacious synergies from different technologies and scientific sectors in order to create an applicative and interdisciplinary system to tackle emergencies and to address healthcare, clinical and epidemiological situations. As a Decision Support System, the ECO4CO service offers several capabilities to the end-users and the competent authorities. It provides an analysis in near real-time of the epidemiological spread and trends of the COVID-19 disease against geographical distribution (from national level to district detail). It can help to prevent the outbreak of new possible clusters of infection cases. It allows identifying movements and changes in urban and suburban areas, monitoring aggregations and events (planned or spontaneous) involving people that are potentially exposed or positive to COVID-19. From an economic point of view, many resources can be saved. Industries and Small Medium Enterprises (SMEs) could avoid lockdown measures by preventing the spread of the disease and timely managing possible crisis due to personnel affected by COVID-19. These measures would prevent a huge economy loss, which would be dramatic in case of several waves of the pandemic. Most relevant for the healthcare of the population, the healthcare system could manage in advance the raise of critical situations and prevent the collapse of medical centres. This can be performed with the prediction of medical equipment needs so that they can be collected where available beforehand. The global effect will be an increased efficiency of the healthcare system with benefits for the sick persons. Finally, such service is further foreseen to provide inputs and benefit for possible future emergencies after testing efficacious geo technological and interdisciplinary solutions [50].

3.6. Geo AI to aid disaster response

A disaster with a huge number of casualties presents a substantial task to all rescuers and support management team. To make the best decisions possible under difficult and bad situations in a fearful and dangerous atmosphere, rapid assistance by whatever means necessary is essential. Disaster management strategies should be capable of promptly collecting data, mapping out the impacted region, and comparing conditions following the initial crisis. Options such as where to park rescue vehicles, processing sites, and first aid equipment must all be considered. Additionally, choices ought to be made on the required equipment, priority allocation along with human resource management to aid rescue efforts. One classic example is the Beirut explosion (Internet source).

In a situation like this, aerial pictures and satellite photographs might be quite beneficial. SAR can infiltrate clouds as well as capture data in any weather with high-resolution. Despite its obvious perks, this notion could be restricted to a research instrument, confined to human observing capabilities. This weakness implies and demands a transition away from human interaction, as well as the application of strong AI and computer technologies. These will enable for the near-real-time automated extraction of important findings such as space-time comparisons of area and object recognition [51].

In their study, Demertzis et al. employed a GeoAI disaster response computer vision system for domain adaptation that leverages memory-augmented deep reservoir computing. Its purpose is to document, map, and identify a catastrophe area using SAR materials. The accuracy of their recommended technique in detecting scenes from remote sensing images was tested using the Space Net Multi-Sensor All-Weather Mapping dataset [50]. This suggests that it might be used in higher-level geographic data processing techniques including interdisciplinary classification, pattern recognition, and monitoring. Spatial mapping was used by Rao [52] to analyze disaster management. A spatial map for identifying disasters was created, and the intellectual ability within each of those algorithms enabled the point and multi-point decision-making systems to be capable of assessing the disaster's potential spread. In order to follow catastrophe occurrences, create maps, and conduct spatial and statistical analysis for disaster management, Huang [53] introduced a cyber GIS framework, which can autonomously synthesize multi-sourced data, like social media and socio-economic data. Tropical cyclones often strike coastal regions across the world, with typically disastrous results. With the use of satellite remote sensing and spatial analysis, several methods and datasets have been developed to collect data aiding in the management of natural catastrophes [54]. Every stage of cyclone disaster administration may benefit from the precise and effective information that remote sensing and spatial analysis can supply [29,55,56]. In order to lessen the effects of upcoming tropical cyclones, remote sensing data and spatial analysis give the necessary knowledge on modifications to ecological parameters and infrastructure as a result of cyclonic impacts [54].

3.7. GeoAI for precision medicine

The medical profession requires quick decision-making and relies on as much data as feasible about a patient's condition [57]. Precision medicine is an attempt to personalize preventive and curative treatments by taking into account genetic, environmental, and behavioral variability [58]. As an application of AI in precision medicine, ML has been employed to determine patient diagnoses and results [59]. Recent research efforts concentrating on the inclusion of mHealth in precision medicine offer prospects for GeoAI integration. The adoption of mobile devices to encourage and enhance healthcare and public health services is referred to as mHealth [60]. One of the research priorities of the NIH BD (Big Data) Center of Excellence for mobile sensor data for knowledge (MD2K) is sensor-activated mHealth noise, which can incorporate data about environmental exposures based on sensors such as noise, light, chemicals, and other variables that amplify the temporal accuracy of precision medicine based on mHealth [61].

Another functional advantage of GeoAI for precision medicine is geo-medicine, which is used to determine the importance of information about the area of an affected person in the assessment and treatment of disability [62]. Healthcare professionals can generate statistics on data centric environmental advertising to warn about environmental issues that may affect the health of human beings. Clinicians can provide patients with environmental hazard information primarily using performance statistics based on where they live and work [63].

3.8. GeoAI for achieving sustainable development goals

There are total of 17 sustainable development goals that are embraced by United nations and its member states. These goals are set in order to eliminate hunger, poverty, maintain good health and harmony among people and secure the earth. Monitoring these goals will be effective when it is done at the community level. Various GeoAI techniques can be utilized in monitoring these goals spatially and at the community level. For instance, GIS based poverty map can be used in monitoring goal 1, geospatial data can be used in agricultural yield estimation and forecasting which helps in

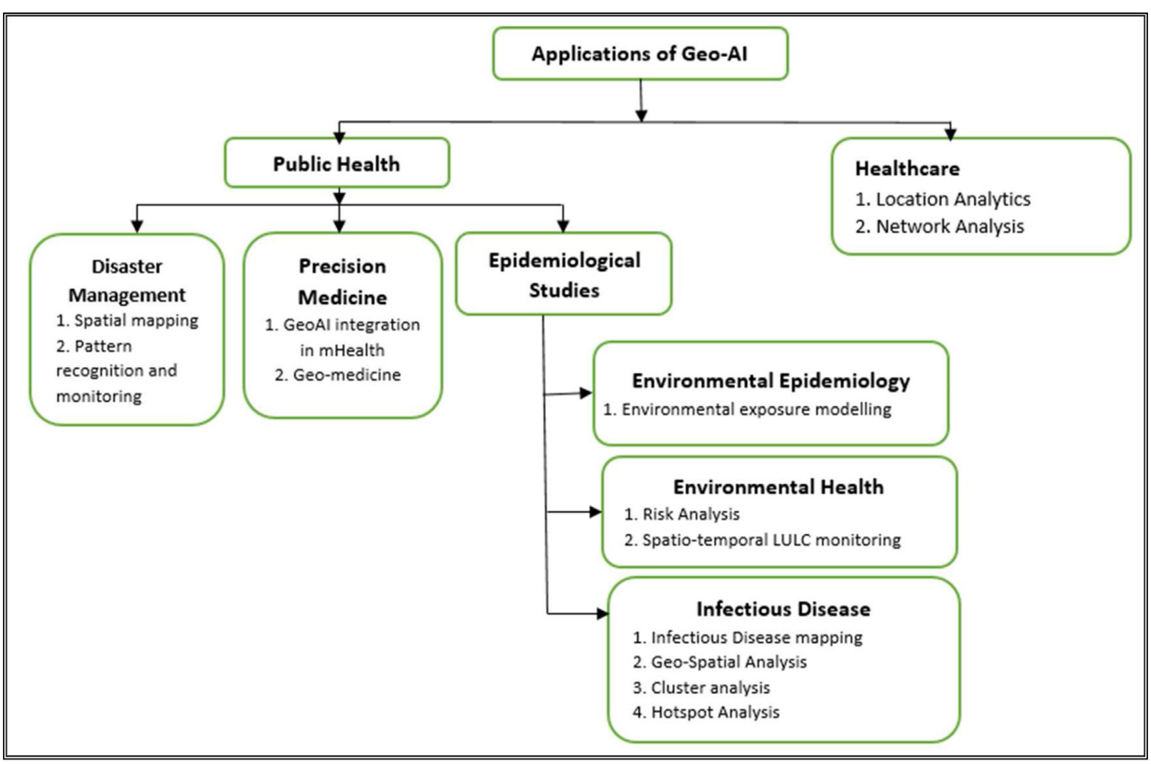

Fig. 6. Flowchart of applications of GeoAI in various health fields.

smart farming which in turn helps in monitoring second goal. The third goal of SDG is to maintain good health and wellbeing and geospatial analysis for examining healthcare system, location of hospitals and distribution and patterns of spread of diseases can be used in monitoring this goal. Similarly other goals can also be monitored using various GIS techniques along with AI algorithms like, finding spatial location of water sources and distribution of water pollution, urban planning, detection of large-scale impact of climate change on Human health etc. which in turn helps in maintain good public health. Fig. 6 shows the application of GeoAI in different Health sectors.

4. Future prospects and conclusion

GeoAI is built on the foundations of ML and DM, which are assisted by high-performance computers. GIS additionally provides the technologies and tools, which permit specialists to illustrate, comprehend, as well as analyze actual occurrences in relation to specific locations. GeoAI is progressively employed to model and portray the environment in which we live. There is also a lot of research being done on using GeoAI for hypothesis creation, new data links, and disease prediction [3,5,6,8].

In this changing world, Changing Geography, Changing Climate directly or indirectly affect human beings in one or other way, sometimes it may catastrophic. With the emerging new and advanced techniques of GIS along with AI algorithms, now health professionals can focus on Geo medicine as well. Geo-medicine is concerned with population health issues and spatial variation in the causes, distribution, prevention and treatment of diseases. While other health professions are particularly about the health challenge to improve the development and longevity of human life. Geo-Medicine is interested in all of those but relating the situations with spatial processes. Geo AI goes beyond current GIS expectations and into the domain of possibility in the not-too-distant future.

This emerging Interdisciplinary science will lead us to sustainable decisions and explore the most suitable solutions to the existing problems. The great majority of SDGs can be effectively observed using geospatial data and techniques. Additionally, the logical conclusions from the use of geospatial technologies provide a strong foundation for policymakers to promote sustainable development at the municipal and regional levels. GeoAI has the potential to transform current geography and geomatics programs by incorporating a GeoAI dimension into modern GIS curricula. Researchers has to identify particular objectives and connect the dots between GeoAI centric approaches to conventional approach. If this integration occurs with advancing technologies, then they may lead us to solutions we are looking for that may impress the policy makers and they take step towards making our future better.

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Nil.

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