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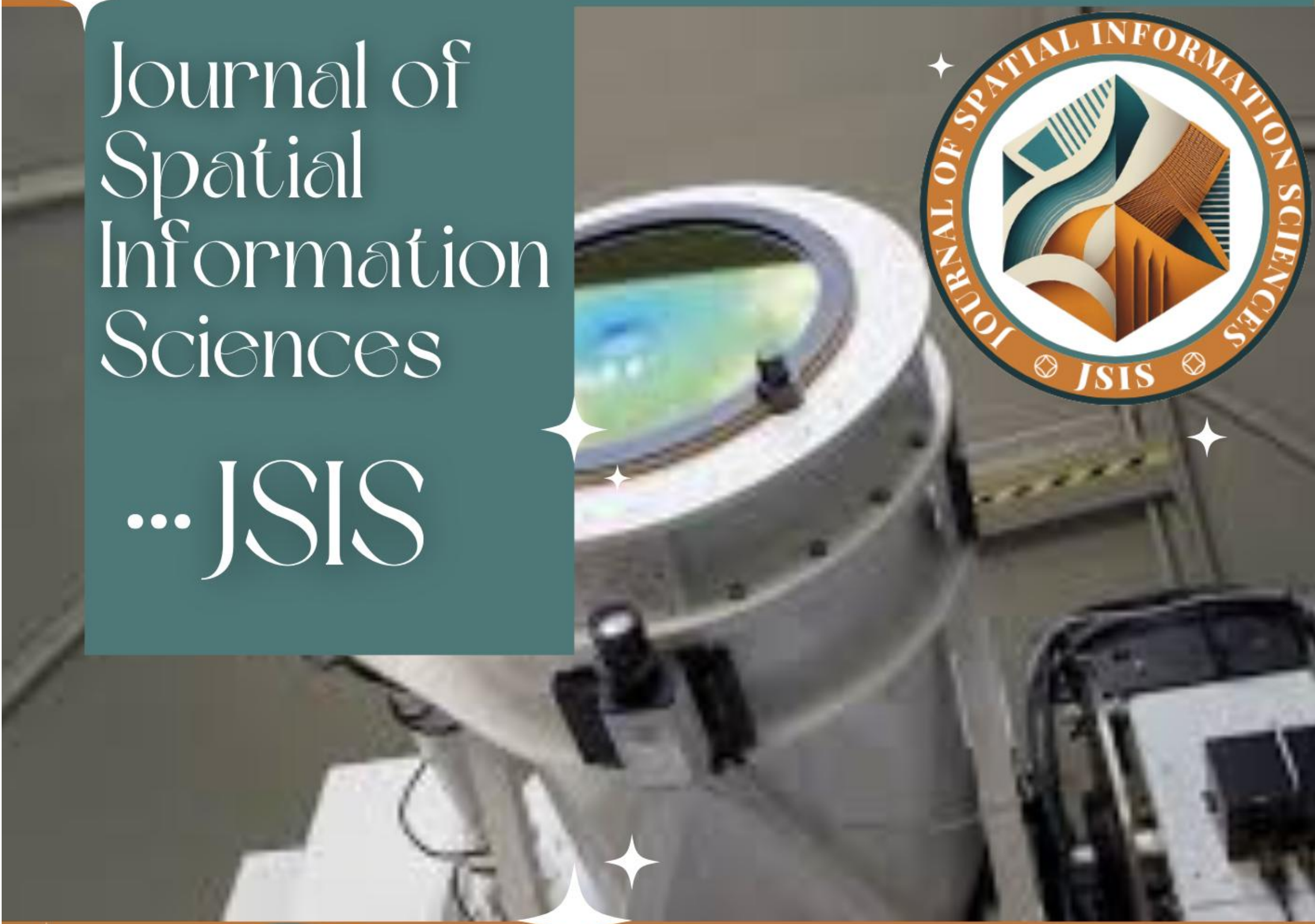

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A REVIEW OF THE CHALLENGES AND PROSPECTS OF ARTIFICIAL INTELLIGENCE APPLICATIONS IN GRAVIMETRIC GEODESY

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Abstract

Gravimetric geodesy is a branch of geodesy that studies the strength, characteristics and effects of the Earth's gravity field as well as its temporal variations in space and time. It also functions as a fundamental approach for understanding the gravitational field of the earth, along with its various applications in geophysical exploration, geoid determination and other geodetic pursuits. Traditionally, scholars have relied on mathematical and physical models, however, with the advent of Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), novel and innovative methods for modern data capture architecture (payloads on satellite, UAS, and airplanes), processing, simulation, animation as well as managing extensive and complex gravity data have emerged. This paper aims to explore the transformative influence of AI on gravimetric geodesy,given its challenges and possible solutions and strategies. AI possesses the potential to significantly improve accuracy and efficiency in data processing; however, obstacles such as data quality, model interpretability and considerable computational demands may hinder its wider adoption. This study proposes several solutions, such as advanced data pre-processing and hybrid AI-geodesy models, alongside explainable AI frameworks and enhanced computational infrastructure. This paper therefore, recommends interdisciplinary collaboration to fully explore and exploit the potential of AI in gravimetric geodesy for sustainable applications in Nigeria and across the regions of the Earth.

KEYWORDS: Gravimetric geodesy, Artificial intelligence, AI applications, AI Challenges and Solutions.

1.0 INTRODUCTION

Gravimetric geodesy, as one of the disciplines in geodesy (the science of determining earth's shape, orientation in space, and gravity field), is a form of science with the goal of achieving the aim of geodesy using gravity data. Geodesy is an important field of study when it comes to analysis of earth's gravitational field and fluctuations, or changes in that field, for numerous scientific and practical uses for geodetic, geophysical applications. Its geodetic studies include geoid modelling and satellite orbit determination, among others, while the geophysical studies lay emphasis on the provision of information on subsurface mineral deposits. Idowu and Abubakar (2013) opined that the geophysical studies could provide the information on the mineral deposit to a significantly greater depth and are logistically simpler to carry out than other methods. It has a crucial function of checking mass distribution at the earth system, which other distribution systems of the earth's structure such as tectonic motion, Glacier and sea levelling systems (Rummel, 2012).

Heretofore, gravimetric geodesy has depended on mathematical models, in particular least square adjustments and spherical harmonics, for the treatment of gravity data from terrestrial, airborne, and satellite sources. Recent missions such as the Gravity Recovery and Climate Experiment (GRACE) and its successor, GRACE-FO, have testified increased accuracy and amount of operationally derived gravitational data that delineate mass redistribution globally over time (Bauret *al.*, 2007). Nonetheless, the increasing size and elaboration of the gravitational data have become unfavorable in the analysis of the data. These methods at times fail to gracefully work within large datasets from multiple heterogeneous sources with varying resolution and noise (Fluryet *al.*, 2006).

Machine learning and deep learning technologies are the AI technologies which have come up as opportunities to solve these challenges. AI approaches have emerged in recent past to improve data analysis through aspects such as data fusion, noise elimination and pattern recognition, which has led to considerable strengths in the gravity field modelling (Shum &Kuo, 2011). However, the utilization of AI technology in gravimetric geodesy contributes to the emergence of unique concerns. Among them, one is the quality and heterogeneity which directly influences the AI training and performance, as mentioned by Xu (2007). Furthermore, several AI models, particularly those with deep learning, are inherently opaque and thereby raise questions of their usability and credibility in fundamental experimental disciplines (Melgar& Bock, 2015).

In addition, another limitation is the computational complexity because the analysis of large gravity data with the help of AI solutions is a computationally intensive process (Andersen &Knudsen, 2009). This paper therefore, aims to examine the application of AI in gravimetric geodesy with a view to discussing the major challengesfacing its implementation and the possible solutions. The paper also discusses the challenges facing the developing field of AI in gravity field modelling and data analysis. In addition, it will put forward new ideas, for instance, superior pre-processing algorithms, convergence frameworks based on AI, geodesy, and AI explanation that may lead to improved gravity models. In other words, participation of both AI professionals and geodesists will only enhance gravimetric geodesy to its full potential that in turn can enhance geodetic as well as geophysical interpretations.

Thisstudy evaluates the challenges facing the application of Artificial Intelligence in gravimetric geodesy, as well as proffers some possible solutions, from modern architecture of data acquisition processes to the execution of rigorous computations for gravimetric data processing and analysis routines.

1.1 Brief historical context of gravimetric geodesy

Gravimetric geodesy is the study of the strength and alteration in the earth's gravity field. It is used in geophysical exploration, determine geoids, and correct the orbits of satellites (Rummel, 2012). Gravimetric data is used where historically it has been obtained by ground digital gravimeters, airborne gravimeters, and seaborne gravimeters, as well as satellite missions, for example, the Gravity Recovery Climate Experiment (GRACE) and, recently launched, their successor, the Gravity Recovery Climate Experiment Follow-On (GRACE-FO). These methods have given meaningful contributions in distribution analysis of masses in the system of the earth (Baur*et al.*, 2007; Nazirova, *et al.*, 2022).

Other techniques of processing data have in the past involved methods which include least-squares adjustments, spherical harmonics and filtering on noise (Koch, 1999). As the technology of satellite grows, the missions such as Gravity field and steady-state Ocean Circulation Explorer (GOCE) present exceptional precision of gravity field data. However, the large quantity and features of gravity data have raised problems for past conventional techniques of data analysis, which in turn has fueled wide use of more complex computational algorithms (Flury*et al.*, 2006).

2.0 EMERGENCE OF AI IN GRAVIMETRIC GEODESY

Machine learning referred to as a sub-field of AI has revolutionized a number of data driven disciplines by automating tasks, managing data, and generating insights that would otherwise be concealed to a human eye. In gravimetric geodesy, it appears that AI is able to add value in analysis and modelling of gravity data through the gain in accuracy, handling large volume of data and real time processing (Shum &Kuo, 2011; Huerta *et al.*, 2021).

Among the first applications of AI in physical geodesy was the use of AI for automation of data elaboration, for instance, for filtering noises from gravity data. Probability-based noise reduction approaches are strictly related to certain conceptions of the noise nature. Nonetheless, there are preprocessed based on the models, AI algorithms like Convolutional Neural Networks (CNNs) can recognize the patterns and eliminate the noise spots without using the above models (Xu, 2007). This renders them highly suitable for gravitational data, where noise landscapes may be tangled and non-stationary.

The fundamental concept of artificial intelligence is based on the development of a system that can perform specified problem solving, reasoning, learning perception and decision making tasks required by human intelligence. Gravimetric data collection techniques have largely moved from terrestrial to space (satellite and airborne techniques) with payloads that are highly driven by structured AI (ML and DL) algorithms/codes for the seamless automation of the entire process (Oguntoye*et al.*, 2023; Pierdicca&Paolanti, 2022). Therefore, AI is an enhancer of speed, quality, and convenience in the entire geodetic and geospatial value chain.

2.1 AI applications in gravity field modelling

Through AI, contributions to gravity field modelling have been achieved that significantly benefits gravimetric geodesy (Oguntoye*et al.*, 2023). The gravity field models are used in defining changes of gravitational field and such applications include; satellite positioning, geoid surface modelling and gravimetric search for minerals among others. Traditionally, spherical harmonics have been used to compute gravity field models, but they struggle to capture local gravity field variations due to their global nature (Rummel, 2012).

Current research has also focused on the application of the gravity field models of the SVM and random forest for the construction of more localized gravity field models in comparison to more general global gravity field model due to their ability to more effectively analyze variations in regional gravity data (Baur*et al.*, 2007). Additionally, though not the traditional DL models, the Recurrent Neural Networks (RNNs) are being applied in the determination of the changes over time of the gravity fields. It also means that rapid movements of geophysical features such as glacier and groundwater are measured with a higher degree of accuracy (Melgar& Bock 2015).

2.2 AI for data fusion and integration

Data fusion which is the integration of data from different sources is another key domain where AI brings a lot of difference (Alteriis*et al.*, 2023; Jin-Jian*et al.*, 2023). Flury*et al.* (2006) has suggested that in gravimetric geodesy, the data derived from airborne and satellite data and terrestrial data must be combined in order to give a gravity model. However, differences in data resolution, measurement techniques, and noise levels make this task challenging.

Areas of data fusion applications has also been incorporated by employing AI algorithms especially in ensemble learning methods which employs an ability of learning from different data sources and automatically corrects the internal data discrepancies (Shum &Kuo, 2011). For instance, AI methods have been applied in combination with data from both GRACE and GOCE satellite missions as well as gravity data from the ground to increase the precision of gravitation field models within regions where just satellite data is inadequate (Rummel, 2012). In addition to more accurate, these integrated models offer a better representation of earth gravity field.

2.3 AI for temporal gravity variations

Perhaps the most significant of all the areas where AI is likely to be highly beneficial to gravimetric geodesy is in the examination of temporal changes in the gravity field of the earth. These changes, which take place due to such processes as mass redistributions connected with the melting of ice, or formation of new reliefs owing to earthquakes and land subsidence, are hardly amenable to quantitate estimations based on conventional approaches. Artificial intelligence techniques, especially the same set of Deep Learning algorithms include LSTM networks have been used for the analysis of the temporal data of gravity measurements in order to analyze the patterns that may be associated with these geophysical events (Melgar& Bock, 2015). Since the GRACE satellite data is sequential data, astronomers have found the LSTM networks efficient in monitoring temporal variations in the earth’s gravity field data. This has enhanced reliable forecasts of mass variations for example, ice sheets or ground water level changes, which are essential in assessing the effects of climate change and natural disasters (Shum &Kuo, 2011).

3.0CASE STUDIES THAT DEMONSTRATE THE REAL-WORLD APPLICATIONS OF AI IN GRAVIMETRIC GEODESY

These give a general picture of where within gravimetric geodesy AI is being used and hence where such advantages regarding accuracy, speed, and forecast are liable to emerge. Every one of them tries to explain the applicative value of AI to seek enhancement of regional gravity field modelling, to develop natural disaster preparedness, and to aid resource exploration.

Case study 1: The application of the improved gravity field modelling in the context of Greenland ice mass observations with the use of Artificial Intelligence. Gravimetric investigations have been made on Greenland's ice sheet because of the extent to which it contributes to global sea-level fluctuations. Ice mass change data was obtained from the GRACE and GRACE-FO missions Explorers, but such data was in most cases complex and needed to be filtered and integrated from variety sources. Here, AI techniques, particularly DL algorithms were employed to smooth the noise in gravity field models as well as to integrate satellite and terrestrial observations. The research also used neural networks for error correction and better spatial resolution of gravity data measurements. The models supplemented with AI offered higher definition results of the gravity field which improved on the ability to monitor the melting ice mass in Greenland. This demonstrated that AI could substantially attenuate noise in the satellite data while enhancing the comparability of the results provided by different sets of data. The applied value was the enhanced ability to predict Greenland's ice mass loss and its contribution in global sea level changes (Baur*et al.*, 2007).

Case study 2: Application of gravity data for AI-driven detection of the Japan earthquakes. Seismic elicitation approaches used in identifying earthquakes have in the past issued late alerts though they can be used to detect small earthquakes that could be devastating. Accelerometric data has all the possibilities to enhance early earthquake prediction, still processing gravimetric data in real-time has its problems. Aresearch in Japan used AI algorithms to analyze gravimetric data from terrestrial stations and satellites in order to estimate future earthquake (Shafapourtehrany*et al.*, 2023; Akhoondzadeh, 2024). Historical gravimetric and the seismic data-fed ML models could identify preparatory gravitational anomalies before earthquakes. The AI driven models demonstrated small to medium scale earthquakes with better mean lead times averaging well over the seismic methods. This approach showed that AI had the capability of improving current gravimetric geodesy to help advance early warnings systems for earthquakes and to aid disaster prevention and response in earthquake prone zones (Melgar& Bock, 2015).

Case study 3: Application of Artificial Intelligence for Gravity Anomaly Delineation in Oil and Gas Field. Magnetic gradiometry is one of the major techniques used in the oil and gas exploration, by which density changes in sub-surface may suggest the location of petroleum deposits. However, earlier approaches to analyze such gravity data are cumbersome and involve in huge amount of interpretation. More recently, authors used AI-based models to perform the automatic identification of gravity anomalies associated with oil and gas resources. These CNNs were trained on both, synthetic and real gravity data invariably to identify features related to subsurface structures. The integration of AI in this context was beneficial in depicting the gravity anomalies which typically would take a lot of time to identify hence reduce the cost of explorations. AI derived models gave information, which was not obtained through traditional approach thus enabling efficient decision-making in the exploration process (Baldwin &Trivedi, 2018).

Case study 4: AI-optimized data fusion for gravity and altimetry in coastal areas. Some of the complications experienced in making gravimetric measurements along the coastline are complex owing to water presence and complicated, irregular topography of the region and influence from other meteorological factors. More specifically, traditional gravity field models have difficulties in terms of accuracy in these areas. To boost the data fusion of satellite altimetry with the terrestrial gravimetric data in coastal areas ensemble learning techniques has been used in the AI techniques. The AI model was trained to optimize the integration of data with varying resolutions and quality. The AI-optimized data fusion model resulted in significantly improved accuracy of gravity field representations in coastal areas, leading to better models of sea level changes and coastal dynamics. This improvement is quite beneficial in climate change research and coastal applications where precise gravity data are essential (Andersen & Knudsen, 2009).

Case study 5: The methodology of regional gravity field recovery by means of integrated AI and GRACE. The GRACE mission is helpful for studying temporal gravity field changes on Earth but there are problems if used only for regional gravity field modelling, especially when having to work with numerous data gaps or complicated topography. AI-powered regional gravity field recovery techniques were applied to enhance GRACE data for regional applications. Regional gravity gradients were learned, with the neural networks' help, and systematic error in data was mitigated. This approach was more favorable concerning producing more realistic models of the regional gravity fields particularly areas of complex topography. The use of AI in the gravity field recovery enhanced the regional studies by providing the much needed better estimates of small scale features such as the tectonically active regions or changes in water mass distribution. The improved models offer better clarification of the regional geophysical activities that enhanced the prediction of events such as earthquakes and glacial movements (Rummel*et al.*, 2011).

3.1 Challenges in using AI for gravimetric geodesy

The use of Artificial Intelligence (AI) in gravimetric geodesy has provided new avenues for data capture in satellite gravimetry/satellite sensing and aerospace geodesy, andexecuting the analyses of a broad and intricate assortment of datain general. However, there are some issues that still require solutions before the AI techniques can be sufficiently scaled up and cascaded for gravimetric applications and analysis. AI thrives on data, but gravimetry suffers from dearth of multi-temporal data and databases at regional and local scales, this makes the deployment of AI tools effectively unrealistic. Other challenges, as described below, include span data-related problems, algorithm defects, computational costs, and issues related to model interpretability and acceptance among the geodetic community.

Data quality and availability: The one common problem that arises is data quality. Such gravity disturbances contain noise origin from instrumental and environmental factors as well as from dissimilarities in between different methods (Andersen & Knudsen, 2009). Many AI models consider data a prominent characteristic, including ML and DL methods; as such, when data is inconsistent, AI will likely present unreliable or biased findings. Additionally, gravimetric data are collected from scattered instruments such as terrestrial, seaborne, airborne, and satellite gravimeters, which possess different spatial /temporal resolutions. Syntacting such data into a unified dataset which is friendly for development of AI models may be quite complex. For example, satellites such as the ones from GRACE offer full coverage of the earth but at a lower resolution, whereas the gravimetric approach on land gives high resolution data at a very small area of the globe (Flury*et al.*, 2006). AI models need preprocessing and calibration to overcome these differences in order to integrate the data computed from the different sources logically and rightfully (Shum &Kuo, 2011). Further, labeling of data which is compulsory for constructing the training dataset of the supervised learning is often a challenge in the gravimetric geodesy. Global gravity field measurements are very limited in many sectors, especially in regions that are inaccessible or in the sea, resulting in voids in the databases utilized in modelling. This makes it difficult for AI algorithms to be trained comprehensively and thus when trying to predict or model gravity field variations in regions that were sample sparingly for instance, (Xu, 2007).

Computational complexity and resource demand: DL models, as well as other AI models require a certain amount of computational resources. Applying AI methods for processing gravimetric data, especially of regional and global scales, can be computationally intensive implying the need for high performance computations (HPC) and parallel processing (Baur*et al.*, 2007). The training of DL models can be characterized by looping through massive volumes of data, tweaking thousands to millions of model parameters. This can be very time consuming and demands a lot of computational resources which in turn makes accesses of AI solutions in gravimetric geodesy difficult for institutions without powerful computational infrastructure. Furthermore, with new satellite missions such as the GRACE-FO and GOCE soon to release more accurate gravity data, the amount of data in question continues to expand. From these the two big datasets it is clear that in order to manage such type of loads storage facilities are not only a necessity but also the algorithms that are used to handle them have to be equally efficient to handle the increased data load (Melgar& Bock, 2015). Developing such algorithms and ensuring that AI models remain computationally feasible is a major challenge for researchers working at the intersection of AI and gravimetric geodesy.

Lack of interpretability and the "Black Box" problem: A challenge facing AI technology, particularly DL models, is the lack of interpretability, commonly referred to as the "black box" problem. In contrast to methods used in gravimetric geodesy that can be traced back to physical principles and formal mathematics, AI principle often do not specify how a solution was arrived at (Xu, 2007; Xing &Sieber, 2023). For example, neural networks which are used in many AI applications need millions of internal weights that control the ability of the network to minimize prediction errors; nevertheless, mechanical connection of these weights in respect to physical phenomena in the earth's gravity field is not feasible. This non-interpretable structure may pose a problem in applying AI techniques in gravimetric geodesy. Such practitioners very often under classical geodetic approach that provides physical interpretation of results and therefore might be reluctant to use AI models when physical processes behind them are not clear. In particular, in such scientific disciplines where precise results and demonstration of their valid and viable are essential, the lack of ability of an IA model to explain results of calculations will call into question the result and their reliability. There are ongoing researches to present methods of XAI whose goal is to increase the interpretability of these AI models. XAI techniques include methods of explaining a model's decision making or providing easier interpretations of complex versions of the model. However, these concepts are still in their developmental stage and applying the above approaches to the complicated models as applied in gravimetric geodetic studies is still a challenge as indicated by Rummel (2012).

Generalization across diverse geophysical conditions: AI models, especially those trained on specific datasets, may struggle to generalize across different geophysical conditions. For example, a model, established based on gravity data from one area, for example, the Greenland ice sheets probably does not hold when applied in other areas with a different geophysical background, for example, a tectonically active region in the Pacific (Flury*et al.*, 2006). This restriction prevents generalized implementation to extended scope such as global or any large scale investigations of the AI models. This generalization problem is further exacerbated by the dynamic nature of the earth's gravity field. Complexities in specific extras caused by temporal variations including seasonality, of water storage, or long-term ice mass loss etc., forcing the AI models to also capture the temporal trends in the data. Although temporal models such as LSTM can be applied to the current problem, the major issue arises on how to train the models to generalize well across the different geophysical conditions (Melgar& Bock, 2015).

*Data security and privacy concerns:*When it comes to data-sensitive researches like national gravity networks or restricted satellite missions, application of AI opens concerns over data protectiveness and confidentiality. In this regard, AI models that are trained on such data may reveal such information by: Interpolating sensitive information from its model's outputs as well as by The nature of model training and model validation (Andersen & Knudsen, 2009). Since AI is gradually being deployed as part of international geodetic frameworks, there is the challenge of protecting the AI models of the relevant data-processing pipelines from malicious interference or appropriation.

*Skill gap and interdisciplinary collaboration:*As it has been already mentioned, AI integration in gravimetric geodesy implies interaction between traditional AI experts and geodesists; however, such an interdisciplinary cooperation leads to the emergence of the so-called skill gap. With regards to the second and third objectives, a large amount of geodesists have no knowledge of AI algorithms and can hardly integrate these methods into their studies with the help of related AI knowledge. On the other hand, AI researchers may lack the geodetic expertise required to apply their models effectively in this domain (Baur*et al.*, 2007). These skills must be bridged by means of cross-disciplinary educational as well as training initiatives that would include both AI and geodetic experts. It can assist in advancement of the corresponding AI models to introduce gravimetric geodesy to conditions for which it is examined as well as to ensure the respect of geodetic principles during the invention of AI models.

3.2 Solutions for the challenges and future directions

The application of AI in gravimetric geodesy has some limitations; however, there are good opportunities to advance in achieving the goals when finding specific problems and forming inter-academic cooperation. Practical solutions to these challenges and suggestions for future directions are outlined below.

*Improving data quality and integration:*A critical step in addressing AI's data related challenges in gravimetric geodesy is improving the quality and consistency of the datasets. This will be achieved by the implementation of advanced data preprocessing techniques. For example, in data augmentation, which is used as an approach to increase the diversity of training data since data with low gravity observations are scarce in most areas (Flury*et al.*, 2006). Techniques of noise reduction incorporating AI like denoising autoencoders or Generative Adversarial Networks (GANs), greatly enhance the quality of gravimetric data before integration into AI models (Xu, 2007). The use of AI to improve data fusion techniques involves collecting measurements from different platforms, like airborne and terrestrial as well as satellite measurements. For instance, the ensemble learning methods, the fusion neural network based algorithm can medium data with the dissimilar resolution for establishing the more coherent and precise gravity field model (Shum &Kuo, 2011). They could help lower the effects of noisy or inconsistent data input in AI outputs and enhance their usefulness.

Leveraging High Performance Computing (HPC) for AI models: Through HPC solutions, the requirement demand for computational of AI models especially those involving DL algorithms can be met. Government, research institutions and universities are procuring HPC for which it is making costly HPC resource available for AI based gravimetric geodesy study. AWS & Google Cloud Services present finely granulated solutions that can be used to process enormous amounts of gravimetric data in the absence of having to invest in own physical infrastructure (Andersen and Knudsen 2009). Besides cloud utilization it is necessary to implement efficiency measures for such solutions as AI. Some of the approaches like model pruning, quantization and parallel processing can actually lighten the DL model, and hence these can be implemented for geodetic real time applications (Melgar& Bock, 2015). Such optimizations may contribute to close the gap between the computational demand that AI imposes and the constraints of many researchers.

*Advancing explainable AI (XAI) for gravimetric geodesy:*The development of XAI techniques is essential for addressing the "black box" problem in AI models used for gravimetric geodesy. In general, XAI methods is the branch of AI, whose purpose is to explain the decision-making processes of the AI model to the human user (Doshi-Velez & Kim, 2017). For example, saliency maps that show which segments of input data have the most significant impact on the final AI model decision, could be applied to gravimetric geodesy to determine which features in gravity data contribute to some particular prediction or classification. Furthermore, the inclusion of physics-based AI models also have the potential for unification of conventional geodetic techniques with the advanced AI models. These models include physical constraints into the AI prediction such that the results of artificial intelligent models are in compliance with geophysical laws (Karpatne*et al.*, 2017). Such an approach could help enhance the interpretability and robustness of AI models of the Earth based on the synergy of machine learning and well evidenced geodetic theories. However, equal and even more attention should be paid to the education and training of geodesists to employ these tools in practice. The generic promotion of participation in workshops, conferences, and online courses related to XAI methods for geodesy would serve to increase understanding of AI techniques and their increased applicability in gravimetric geodesy (Rummel, 2012).

*Enhancing generalization through transfer learning:*How can AI models be made more generalizable across geographical conditions? There is one way; the use of transfer learning. This include acquiring of large and well annotated databases from defined areas as well as fine-tuning of the acquired models for their use in areas with limited databases or of different geophysical characteristics (Pan & Yang, 2010). This approach enables models to get knowledge from the existing data set and apply the knowledge in the other set without requiring new training thus making the models to generalize. In gravimetric geodesy, transfer learning can be used to develop gravity field models that perform well across different geophysical settings, from polar region to tectonic zone. So, training and modelling of such AI algorithms on missions like Global Gravity Recovery And Climate Experiment (GRACE) and Gravity Field and steady-state Ocean Circulation Explorer (GOCE), will help the algorithm learn the global fields of earth's gravity needed for local studies in regions where there is limited data (Rummel, 2012).

Ensuring data security and privacy: In connection with these issues, regarding gravimetric geodesy, it is necessary to establish rigorous data management policies. The big data integrating proprietary or national gravity datasets with AI should be encrypted or anonymized as much as possible (Andersen & Knudsen, 2009). Furthermore, adopting federated learning approaches, which enable AI models to be trained on distributed datasets without transferring raw data to centralized servers, can help protect sensitive information (Kairouz*et al.*, 2021). By using federated learning, geodetic institutions may also work together on some projects without necessarily sharing their data with others.

*Bridging the skill gap through interdisciplinary collaboration and education:*To summarize the views expressed in this survey and in the current literature, we could agree with the statement that the successful incorporation of artificial intelligence in gravimetric geodesy will critically rely on the synergistic relationships between AI AI and geodesists. Closeness of the skill gap needs not only multidisciplinary teams but also specific training courses that familiarize geodesists with AI methods. In geodesy investigation, universities and research institutions should establish special artificial intelligence courses focusing on geodesy including the topics of ML, DL, and data fusion techniques for gravimetric purposes. Geodesists may get more informed and aware of the role and impact metering systems and other AI-driven solutions they will benefit from through holding joint AI-geodesy workshops and conferences. Such efforts would afford an opportunity for researchers in this field to exchange knowledge, define uniform terminology of use in gravimetric geodesy, deliberate on techniques applicable in gravimetric geodesy and generally address issues unique to the use of AI in gravimetric geodesy (Flury*et al.*, 2006).

*Future directions for AI in gravimetric geodesy:*Developments in gravimetric geodesy in the future are therefore likely to include improvements in the data processing in real time, the global gravity field observance, and the model predictions of the physical events. With the advancement of the models of AI, the inaccuracies of measuring even a micro variation in the earth's gravity field could make way for a more accurate prognosis of major earth events including earthquakes, volcanic activities, and ice mass. Moreover, it is expected that the use of gravimetric data acquisition and analysis that will be prompted by artificial intelligence automation will also grow heavily. Special devices might be Autonomous systems like drones or Unmanned Aerial Vehicles (UAVs which) could possibly be fitted with gravimetric sensors based on Artificial Intelligence and gather real time data where conventional methods are not feasible (Baur*et al.*, 2007). These technologies are still being advanced to provide greater definition and wider coverage of gravity field measurements.

4.0 CONCLUSION

Gravimetric geodesy can significantly improve accuracy and facilitate measurement by leveraging artificial intelligence. Artificial intelligence provides robust methodologies for analyzing large sets of data which increases the accuracy of models, and facilitating real-time predictions of changes in the Earth's gravitational field. The methodologies of machine and deep learning have provided solutions in addressing several conventional obstacles encountered in gravimetric geodesy, encompassing limited data availability, computational complexities, and the necessity for predictive modelling of geophysical oddities. However, the utilization of artificial intelligence within gravimetric geodesy is accompanied by its own set of challenges.

Problems connected with data quality, computational intensity of demand for AI models, capacities to comprehend solutions to be produced by AI technology and generalization of such models at various geophysical conditions still remain the major challenges. Furthermore, the competence gap between AI experts and geodesists to fully demonstrate AI potentials in gravimetric geodesy is also an issue. To address these challenges, concerted inter-disciplinary collaborative efforts need to be made in education and cooperative research.

In particular, integrating the processes of preprocessing and fusing of datasets with optimal computing resources and explainable AI approaches, the computer scientists or rather the geodetic professionals will be able to make use of AI to enhance the performance, speed and forecast abilities of gravimetric models. In addition, working in multidisciplinary teams and filling the gap between AI experts and geodesists will be crucial for the practical use of AI in gravimetric geodesy. Hence, the Solutions to AI-driven developments in future gravimetric geodesy are expected to make it possible to monitor the gravity field of the Earth more accurately in real time, enhance the understanding and forecasting of natural disasters, and even increase the scope of data collection through robotic systems.

Recommendations

The following recommendations are suggested to enhance the integration of AI in gravimetric geodesy:

1. Allocate resources towards achieving better data quality and integration through improvements in data gathering techniques for all gravimetric measurements including terrestrial, seaborne, airborne and satellites. Particularly, the use of advanced preprocessing techniques in order to reduce noise and differences which exist among datasetspromote the application of artificial intelligence noise filtration and data merging in the global gravity field models to improve the quality of multi-source gravitational data.
2. It has been emphasized the importance of promoting High-Performance Computing (HPC) for AI development. HPC infrastructure capable of servicing AI-enabled gravimetric geodesy models must therefore be funded by governments, academic institutions, and research organizations. This means taking into account cloud-based solutions for institutions with limited resources and developing optimized AI algorithms that require less computational resources. Explore model pruning, quantization, parallel processing, etc., to add accessibility of AI models to be more efficient for widespread use.
3. Research on methods that enhance transparency and interpretability in AI models: Advancing explainable AI (XAI) in geodetic applications in gravimetric geodesy. Aiming to foster trust & trustworthiness and hence the uptake of AI in geodesy, this effort seeks to bring together tools from the geodetic community. Moreover, it involves exploring physics-based AI models, which combine geophysical laws and AI algorithms (that adhere to geophysical principles) and, so, they are confirmable to the existing laws.
4. Fostering interdisciplinary collaboration and education, including establishing educational programs and workshops that bridge gaps between AI researchers and geodesists to foster shared understanding and synergistic work. This includes both training geodesists on AI techniques that can be used to address challenges in their discipline and educating AI researchers on the fundamentals of geodetic science. Also,

it is about promoting joint research projects in order to tackle specific geodetic problems with the help of AI, what is intended to create synergies between geodesists and AI experts.

5. Using transfer learning to improve model generalization involves applying techniques that enable AI models to effectively adapt to different geophysical conditions. This approach can reduce the need for retraining in regions with sparse data, ultimately boosting the reliability and flexibility of AI models in various environments.
6. To ensure data security (and privacy) in AI applications, it is crucial to implement robust data security protocols within governance frameworks: this is especially true when dealing with sensitive or proprietary gravimetric data. However, exploring federated learning approaches can enable decentralized AI model training, although it requires careful consideration, because maintaining data privacy can be challenging.
7. Exploring future innovations in AI-driven geodetic technologies involves investing in the development of autonomous systems, such as AI-equipped drones and UAVs, to collect gravimetric data in remote or hard-to-reach areas. These advancements can improve the accuracy and range of gravity field measurements. Additionally, there is potential in using real-time AI applications to predict geophysical events like earthquakes, volcanic eruptions, and ice mass loss, which can greatly enhance disaster preparedness and climate monitoring efforts.

References

Abubakar, T. & Idowu, T. O.(2013). Numerical investigation into the double Fourier analysis for determining the quantity of underground mineral deposit.*International Journal of Civil, Structural, Environmental and Infrastructure Engineering Research and Development (IJCSEIERD), 3*(2), 145-154.

Akhoondzadeh, M. (2024). Earthquake prediction using satellite data: Advances and ahead challenges. *Advances in Space Research, 74*(8), 3539-3555.https://doi.org/10.1016/j.asr.2024.06.054

Alteriis, G., Ruggiero, D., Prete, F., Conte, C., Caputo, E., Bottino, V., Fabiani, F. C., Accardo, D., &Moriello, R. S. (2023).The Use of Artificial Intelligence Approaches for Performance Improvement of Low-Cost Integrated Navigation Systems.*Sensor, 23*, 6127.https://doi.org/10.3390/s23136127

Andersen, O. B., & Knudsen, P. (2009).The role of satellite altimetry in gravity field determination in the coastal zone.*Geophysical Research Letters, 36(L02602)*, 1-6. https://doi.org/10.1029/2008GL036799

Baldwin, R. T., &Trivedi, M. (2018). Applications of machine learning in geophysical data analysis: A case study from oil and gas exploration. *Journal of Petroleum Science and Engineering, 170*, 199-207. https://doi.org/10.1016/j.petrol.2018.06.013

Baur, O., Kuhn, M., & Featherstone, W. E. (2007). GRACE-derived ice-mass variations over Greenland by accounting for leakage effects. *Journal of Geophysical Research: Solid Earth, 114*(B6), 1-12. https://doi.org/10.1029/2008JB006239

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning.arXiv preprint arXiv:1702.08608.

Flury, J., Rummel, R., Reigber, C., Rothacher, M., Boedecker, G., & Schreiber, U. (2006).Gravity field determination by the GOCE satellite mission.*Proceedings of the International Association of Geodesy, 129,* 41-52. https://doi.org/10.1007/978-3-540-37210-6_6

Huerta, E. A., Khan, A., Huang, X., Tian, M., Levental M., Chard, R., Wei, W., Heflin, M., Katz, D. S., Kindratenko, V., Mu, D., Blaiskzik, B., & Foster, I. (2021).Accelerated, Scalable and Reproducible AI-driven Gravitational Wave Detection. https://arxiv.org/pdf/2012.08545.

Jin-Jian, X., Hao, Z., Chao-Sheng, T., Lin, L., Bin, S. (2023). Interpretable Geoscience Artificial Intelligence (XGeoS-AI): Application to Demystify Image Recognition. arXiv.org, abs/2311.04940. https://doi.org/10.48550/arxiv.2311.04940

Kairouz, P., McMahan, H. B., Avent, B., Bellet, A., Bennis, M., Bhagoji, A. N., & Zhao, S. (2021). Advances and open problems in federated learning. *Foundations and Trends in Machine Learning, 14*(1–2), 1-210. https://doi.org/10.1561/2200000083.

Karpatne, A., Watkins, W., Read, J., & Kumar, V. (2017). Physics-Guided Neural Networks (PGNN): An application in lake temperature modelling. arXiv preprint arXiv:1710.11431.

Koch, K. R. (1999). *Parameter estimation and hypothesis testing in linear models (2nd ed.).*Springer.https://doi.org/10.1007/978-3-642-58765-8

Melgar, D., & Bock, Y. (2015).Real-time large earthquake source determination using GPS-accelerometer data.*Bulletin of the Seismological Society of America*, *105*(2A), 852-868. https://doi.org/10.1785/0120140232

Nazirova, A., Kalimoldayev, M., Abdoldina, F., Dubovenko, Y. (2022).Optimization of an information system module for solving a direct gravimetry problem using a genetic algorithm.*Eastern-European Journal ofEnterprise Technologies*, *2*(9 (116)), 21–34. https://doi.org/10.15587/1729-4061.2022.253976

Oguntoye,K. S., Laflamme, S. Sturgill, R. Eisenmann, D. J. (2023). Review of Artificial Intelligence Applications for Virtual Sensing of Underground Utilities.*Sensors*, *23*(9), 4367.https://doi.org/10.3390/s23094367

Pan, S. J., & Yang, Q. (2010).A survey on transfer learning.*IEEE Transactions on knowledge and data Engineering*, *22*(10), 1345-1359. doi:10.1109/TKDE.2009.191.

Pierdicca, R., &Paolanti, M. (2022).GeoAI: a review of artificial intelligence approaches for interpretation of complex Geomatics data. *Geosci.Instrum.Method.Data Syst.*, *11*, 195-218. https://doi.org/10.5194/gi-11-195-2022

Rummel, R. (2012). Satellite gravimetry for geodesy. In S. Flury, R. Rummel, & P. Knudsen (Eds.), *Handbook of Satellite Geodesy*, 247-273. Springer.https://doi.org/10.1007/978-3-540-853620

Rummel, R., Yi, W., &Stummer, C. (2011).GOCE gravitational gradiometry.*Journal of Geodesy, 85*(11), 777-790. https://doi.org/10.1007/s00190-011-0500-0

Shafapourtehrany, M., Batur, M., Shabani, F., Pradhan, B., Kalantar, B., &Ozener, H. (2023).A Comprehensive Review of Geospatial Technology Applications in Earthquake Preparedness, Emergency Management, and Damage Assessment.*Remote Sensing, 15*(7), 1939.https://doi.org/10.3390/rs15071939

Shum, C. K., &Kuo, C. Y. (2011).Observation and geophysical causes of present-day sea-level rise.In understanding sea-level rise and variability pp. 256-275.Wiley-Blackwell.https://doi.org/10.1002/9781444323276.ch10

Xing, J.,&Sieber, R.,(2023). The challenges of integrated explainable artificial intelligence into GeoAI.*Transactions in GIS, 27*, 626-645. https://doi.org/10.1111/tgis.13045

Xu, P. (2007). Regularization and Bayesian methods for inverse problems in geodesy.*Journal of Geodesy, 81*(3), 203-213. https://doi.org/10.1007/s00190-006-0105-x