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Research Paper

Converting Drone Magnetic Data to Ground Data Using Artificial Intelligence

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Abstract: Mineral exploration necessitates a comprehensive approach that involves analyzing various geophysical, geological, and geochemical datasets, in addition to employing efficient and effective methodologies. Successfully addressing this challenge involves integrating and analyzing diverse geographic data, which often come in different formats and possess distinct features, with the aid of innovative applications. One promising technique involves utilizing artificial intelligence to convert low-resolution drone-collected data into high-resolution ground data. For this particular investigation, three supervised regression models—linear regression, random forest, and enhanced gradient—were implemented in the Python programming environment using magnetometric data obtained from both UAV and Proton ground devices. After evaluating the statistical results, including metrics such as mean square error and mean absolute error, it was determined that the enhanced gradient model outperformed the others. This model exhibited respective values of 0.0004 and 0.01 for training data, 0.001 and 0.02 for experimental data, and 0.001 and 0.01 for validation data. Additionally, the enhanced gradient model demonstrated stability, leading to its selection as the preferred model for prediction purposes.

Keywords: Airborne geophysics, Magnetometric, Drone, Artificial intelligence.

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INTRODUCTION

Exploration of mineral reserves at ground level poses a significant challenge as direct evidence is often lacking. The identification of these reserves and mineralizations is crucial, given the diverse properties of mineral resources and the complex geological conditions in which they are found [1]. Several techniques have been developed to address this challenge, including geology, geochemical exploration, geophysical exploration, and remote sensing [2]. Among these techniques, magnetic data plays a prominent role in geophysics. Magnetic data can be collected using both ground-based methods, which offer high resolution but are costly, and aerial methods, which provide lower resolution but are more cost-effective. Among the aerial methods, drones have emerged as a preferred choice due to their ability to operate at lower altitudes, resulting in improved accuracy. To achieve optimal results in magnetic exploration while minimizing time and costs, there is a need for an optimal method that bridges the gap between these approaches. In this context, the use of artificial intelligence and a diverse range of algorithms can offer a promising solution, enabling the utilization of magnetic data in a more efficient and accurate manner. Artificial neural networks (ANNs) present an advantage over traditional experimental and statistical methods, as they do not require prior knowledge about the underlying relationship between the data [3]. This makes ANNs particularly well-suited for modelling complex and often nonlinear data, which exhibit significant variability due to their inherent nature. By leveraging the power of ANNs, it becomes possible to develop a new method that can effectively analyze magnetic data, reduce processing time, and provide data with minimal errors.

In 2017, Stephen Cohn et al. conducted a study on Australian Eastern gold mines, where they successfully utilized random forests applied to geophysical data (magnetic and radiometric) and remote sensing to map lithological features. This study demonstrated the effectiveness of random forest in classifying magnetic data [4]. In 2019, Jinfeng Lee et al. focused on air electromagnetic studies and employed four deep convolutional neural networks to analyze the collected parameters. Through the application of artificial and aerial data, this algorithm not only generated accurate depth images but also exhibited robustness to noise [5]. In 2020, John Stephen Kayude and Yusri Yusup utilized a combined Python and Matlab framework in a study conducted in Nigeria. They applied artificial intelligence and data mining techniques to determine, identify, and map the subsurface structure and desired properties of target minerals in the study area [6]. These examples highlight the successful utilization of artificial neural networks in analyzing earth science data. However, previous studies have primarily focused on processing and interpreting the resulting data, emphasizing the need for improved accuracy and cost-effectiveness in the earlier stages.

The objective of this study is to develop a suitable method that leverages artificial intelligence to combine the advantages of both ground and aerial methods. The aim is to achieve high accuracy while minimizing the time, costs, life risks, and coverage limitations associated with traditional approaches. The proposed method should optimize the point-to-point equivalence of the two methods—air and ground—and streamline the necessary processes. The data obtained through this approach can then be further analyzed and interpreted, ensuring more reliable and expedited results compared to existing methods.

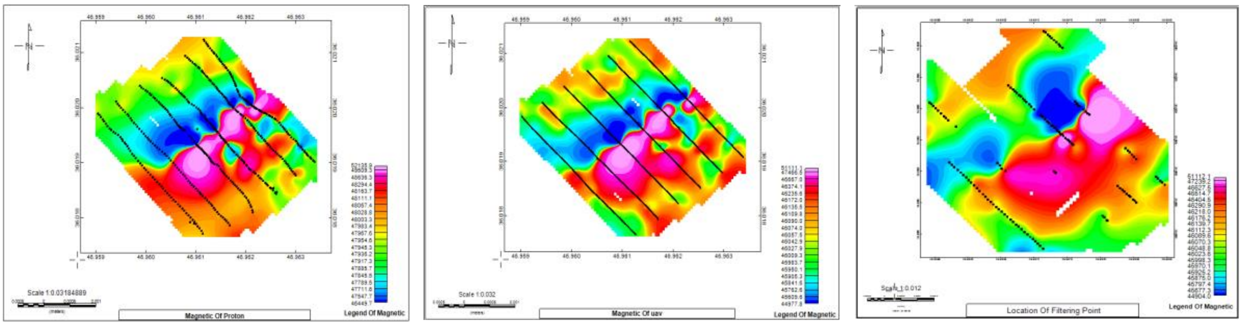
METHODS

The objective of the algorithm in this study is to establish the relationship between the input and output data through the artificial intelligence network. By training the network on the available input-output pairs, it can learn the underlying patterns and associations in the data. Once the relationship is discovered, the trained network can be used to predict the output for new input data. Given the nature of the problem, it is necessary to select algorithms that are capable of performing prediction or regression tasks. Since both the input and output values are specified, the algorithm selection should focus on regression algorithms that can accurately estimate the relationship between the variables.

In this study, three regression algorithms were employed: linear regression, random forest, and gradient boosting. These algorithms were evaluated based on their statistical performance across the training, testing, and validation datasets. The algorithm that demonstrated the best statistical results in terms of accuracy and error metrics across these sections would be considered the superior algorithm for predicting the desired values.

FINDINGS AND ARGUMENT

After collecting and correcting the data obtained from both the UAV and the proton, the magnetic field intensity maps were generated using Geosoft software (Figures 1A and 1B). The initial dataset consisted of 442 points from the proton and 31,382 points from the UAV. To ensure data quality, points within a three-meter range were filtered out, resulting in 129 remaining points (Figure 1C). The longitude, latitude, and air magnetic field intensity were considered as the input data, while the ground magnetism served as the target or output data.



(A) **(B)** **(C)**

Figure 1. A: map of intensity of the magnetic field of earth's harvest data, **B:** aerial with harvest profile and **C:** map of ground and air adaptation points and the intensity of the magnetic field resulting from these points

To train and evaluate the network, approximately 10% of the data (13 points) were randomly set aside as validation data, while the remaining 116 points were split into 80% training data and 20% testing data. The three models (linear regression, random forest, and gradient boosting) were assessed for their performance. Although all models performed well, linear regression showed weaker performance compared to the other two models. Random forest and gradient boosting demonstrated better results, with gradient boosting being selected as the superior algorithm (Table 1). The stability of the gradient boosting network was also evaluated by analyzing the error range and standard deviation, which indicated that the network was stable (Table 2).

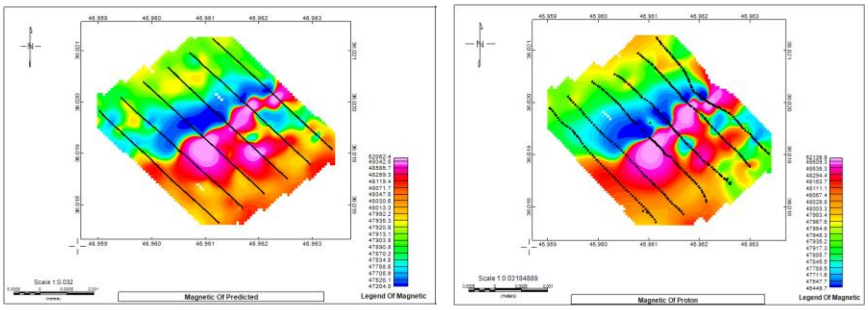
Table 1. The results of the statistical components of the three models implemented in three stages of training, testing, and validation

Model		Mean absolute error	Mean squared error	Median absolute error	Explain variance score	R2 score	Root mean squared error
Random Forest	Train	0.009915782	0.000548293	0.002260187	0.965535858	0.965266866	0.023415661
	Test	0.026276936	0.001992696	0.014750688	0.845481272	0.840042657	0.044639627
	Validation	0.030589285	0.003562773	0.004164696	0.777435639	0.742619828	0.059688967
Liner Regression	Train	0.02549339	0.002157063	0.012479316	0.863354905	0.863354905	0.046444196
	Test	0.035233822	0.003296804	0.019957522	0.738483457	0.735359586	0.0574178
	Validation	0.035782305	0.003635427	0.015244726	0.746539572	0.737371167	0.060294504
Gradient Boosting	Train	0.012999734	0.000406561	0.007611715	0.974245252	0.974245252	0.020163368
	Test	0.025387113	0.001233268	0.015777321	0.901472653	0.901003333	0.035117917
	Validation	0.019955882	0.001226281	0.009685084	0.932825116	0.911411546	0.035018302

Table 2. Statistical results of the Gradian Graduate Network Stability Test

	Minimum	Maximum	Average	Standard deviation
Train	0.009605411	0.023519841	0.018394747	0.002349633
Test	0.014355825	0.178974683	0.048994088	0.032010111
Validation	0.017289743	0.138338533	0.04521458	0.029094517

In the final step, the complete set of aerial data (31,382 points) was input into the gradient boosting network for prediction, resulting in the generation of predicted output data. These predicted data were then transformed into a magnetic intensity map using Geosoft software and compared with the magnetic intensity map obtained from the proton. The comparison revealed a high degree of agreement in terms of the location, intensity, and shape of the magnetic anomalies in both maps (Figure 2).



(A) **(B)**

Figure 2. A: map of intensity of magnetic field of earth harvest data with harvest profile and **B:** magnetic square intensity map of development of gradient boosting network with harvest profile

CONCLUSIONS

In the current era, the rising costs and challenges associated with discovering new mineral resources have necessitated the development of improved approaches to mineral exploration. Artificial intelligence has emerged as a promising solution for solving problems that lack specific mathematical relationships and where causation is not clearly defined. In this study, magnetic data collected by a drone-connected sensor were processed using Python programming to convert the data into ground data. The resulting magnetic intensity map was then compared to the map obtained from ground data collected by a proton magnetometer in Geosoft software. To ensure data quality, a filtering process was applied to the aerial and ground data, removing points that were less than 3 meters apart. This filtering reduced the dataset to 129 data points. A validation dataset comprising 10% of the total data was randomly selected, while the remaining data was split into 80% for training and 20% for testing. Three models—linear regression, random forest, and gradient boosting—were evaluated for their performance in converting the aerial data to ground data. Among these models, gradient boosting demonstrated superior statistical criteria compared to the other two models and was therefore chosen as the optimal model for projecting and forecasting the aerial data. The gradient boosting model exhibited an average squared error of 0.0004 and an average absolute error of 0.01 in the training data. In the testing data, the corresponding values were 0.01 and 0.02, respectively. For the validation data, the model achieved an average squared error of 0.01 and an average absolute error of 0.01. Stability tests confirmed the reliability of the gradient boosting model, as indicated by low fluctuations in root mean square error (RMSE) values and a low standard deviation across the training, testing, and validation data. Finally, the complete set of aerial data was converted to ground data using the gradient boosting model. The resulting ground data was compared to the proton data as a magnetic intensity map, demonstrating the accuracy and efficacy of the selected regression approach. Both maps exhibited high similarity, affirming the accuracy of the conversion process.

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