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Integrating AI With Remote Sensing For Mineral Prospectivity Mapping

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Abstract–*Mineral prospectivity mapping (MPM) is an essential part of mineral discovery, which has conventionally gone through a process dependent on geoscience experience and manual data interpretation. Due to the swift development of remote sensing-based technologies and artificial intelligence (AI), in particular, machine learning (ML) and deep learning (DL), the study of the mineral-rich zones has undergone a paradigm shift. The proposed method of incorporating AI in remotely provided sensory data can be used to automate and improve the precision of MPM, so this paper tries to discuss that. The approach relies on spectral, geological, and topographical data, which are satellite-derived and processed via the application of supervised machine learning algorithms, to provide the indication of the priority of potential mineral areas. The suggested system was applied on a well documented area of mineralization where the results have shown that the effectiveness of AI models to the conventional method is far superior to the traditional in terms of accuracy of the prediction and spatial generalization. The paper demonstrates the usefulness of such an integration that could be used as an aid by geologists during decision-making exercises reducing field survey expenditures and maximising the exploration expenses.*
Keywords– *Mineral Prospectivity Mapping, Artificial Intelligence, Remote Sensing, Machine Learning, Geological Exploration, Supervised Classification, Data Integration.*

I. INTRODUCTION

The world of industrial development is anchored in mineral resources, and this is all that supports infrastructure, electronics, and renewable energy systems. Due to the ever-increasing demand of metals, rare earth elements in the world market, especially as the world moves to green technology, efficient and precise mineral exploration is more important than ever before [7]. Conventionally, mineral exploration is an expensive (and risky) endeavor, which relies on the inferential analysis of geological, geochemical and geophysical data by the experts. Most initial level exploration operations are run on manual mapping and subjective geologic interpretation and this sometimes takes too long and is error prone.

With the introduction of satellite remote sensing, a new phase in the observation and the perception of the earth surface has been a revolution. Such satellites as Landsat, ASTER, Sentinel-2, among others, offer multi-spectral and hyperspectral image processing which has the potential to capture the chemical and structural components of the earths crust. The datasets are commonly used to identify hydrothermal alteration zones, lithological boundaries, and structure like faults and lineaments which are very vital mineral deposit indicators. Nonetheless, remote sensing data is usually multi-dimensional and voluminous, thus posing a bottle neck analytical issue. It is even harder to interpret manually long and complex data on a large geographical scale.

That is where Artificial Intelligence (AI), particularly Machine Learning (ML), comes to the rescue as a revolutionary solution. The ML algorithms are able to discover minute patterns and non-linear correlations within data of high-dimension, and this application applies to multiple cases of complex geologic features under remote sensing data. Training the models based on known occurrences of minerals will enable high spatial accuracy in prediction of occurrence of new undiscovered deposits. Random Forests, Support Vector Machines, and Gradient Boosted Trees are effective methods especially in prospectivity modeling because they accept noisy multi-source data and are capable of accommodating the nonlinear relationship [11].

A number of aspects contribute to the fact that the use of AI in combination with remote sensing is a promising paradigm shift. First, the remote sensing provides an extensive spatial coverage that is characterized by regular revisit periods providing up to date surface information. Second, AI makes feature extraction and prospectivity scoring automatable with the required computer power and flexibility. Third, when it comes to visualizing, validating, and integrating model output with additional geological data, geospatial tools can be used to aid smooth execution geo platform for information systems (GIS). Coupled with other tools, these instruments are able to speed up the mineral exploration process, lessen field expenses and considerably lessen environmental interruption by working just those zones that have high possibility [10].

Nevertheless, there are a number of obstacles. The remote sensing has to be pre-processed by way of atmospheric correction, geometric alignment and smoothing of the noise. Besides, the training of AI models needs the ground truth data, which might be scarce in the backhanded areas of exploration. Notwithstanding these shortcomings, on a case study, AI-assisted mineral prospectivity maps have proven to point towards a higher accuracy than the manual method. They also give integratable workflow that fits into various geological environments.

This paper offers a sound, AI-based framework that combines multi-source remote sensing data in satellites in conjunction with machine learning in order to come up with predictive mineral prospectivity. The technical technique includes feature extraction, supervised training, spatial prediction and evaluation performance [12]. An evaluation of the accuracy and usefulness of the framework uses a real-world test case. The aim is not only to come up with a model, it is also to prove a replicable pipeline that exploration companies, governments, and prospector researchers to target effectively minerals.

Such combination of AI and remote sensing may transform mineral exploration into predictive rather than reactive undertaking, i.e. able to reveal mineral-rich areas faster, more efficiently and with increased confidence by helping those making decisions [15].

Novelty and Contribution

The originality of the research is that it is systematic and integrative to the combination of artificial intelligence with remote sensing technologies to generate mineral prospectivity mapping data, which is an area where such hybrid solutions are Godsend even now. As compared to the traditional approaches, which process remote sensing data in a manual manner or use a single source of data, our model offers a comprehensive mineral prediction model by synthesizing satellite imageries, digital elevation models, geological maps and geological structures [9].

The leading insights into this work are:

- End-To-End AI Framework Of MPM: We propose an end-to-end pipeline where we have integrated acquisition of data, feature engineering, training model, spatial prediction, and validation. Such a systematic design makes it reproducible and flexible to other types of minerals and lands.
- Multi-Source Feature Fusion: We utilize the richness of features available through remote sensing: vegetation indices, band ratios, results of principal component analysis, terrain derivates (slope, curvature), nearness to mapped faults, etc. to train models that have much more contextual information available, and therefore better success at classification [13].
- Comparative Algorithm Evaluation: The given work contrasts the Random Forest, SVM, and Gradient Boosting to determine the most suitable model, unlike in the previous researches, which use one approach based on the machine learning method. The validation of the performance is based on a case in the real-world and standard metrics (F1, ROC-AUC, etc.).
- Useful Mineral Targeting Implementation: The work provides an academic methodology transfer to utility by matching the predictive maps on recognized mineral deposits, verifying the predictive overlaps and providing a working example of how exploration is directed through the output as a decision support tool.

- Open Data Usage and Scalability: The remote sensing data used in the application are open-access and the AI framework they use open-source, which makes the method cost-efficient and scalable, accessible to exploration teams operating on a low budget.

This research contribution is not only contributing to the technical debate on the use of AI in geosciences but it also provides a real-world, data-based tool to use in the exploration process in the mining industry; in environmental planning by various organizations and agencies such as the Geological survey [16].

II. RELATED WORKS

In 2022 Y. Kong et al., [14] suggested the mineral prospectivity mapping has changed in a tempered but revolutionary trend through a departure with manual geoscience inference towards data-based modeling. The insertion of remote sensing data into the mineral exploration processes was a remarkable achievement allowing covering larger regions with more spatial and spectral data. The remote sensed imagery on missions like Landsat, ASTER, and Sentinel, have been extensively utilized in detection of alterations of the commodities existing at the surface and in lithological boundaries as well as lineaments or structural boundaries- parameters that cumulatively have been collected painstakingly by field operations.

Early attempts to combine remote sensing with mineral exploration were claim mostly on band ratioing, principal component analysis, and the visual interpretation of false-color composites. Although such methods were successful in helping to identify some of the alteration minerals, they were not predicting and generalising in different geological contexts. Moreover, multidisciplinary nature of most geological environments necessitated integration of multisource data including elevation, geochemistry and geological maps which would not have been effective using conventional image processing algorithms.

As machine learning took a next step, paradigm transformed into the mechanization and quantification of mineral potential mapping. Techniques of supervised classification started out displacing visual interpretation, where models were trained on prior knowledge of where mineral deposits occur and use that knowledge to predict future target zones. The non-linear association among predictor variables and occurrence of minerals was modeled using algorithms like decision trees, random forests, support vector machines, and gradient boosting. These procedures allowed drawing of mineral potential maps that were more objective and accurate [5].

A significant advantage that machine learning had was the capability of processing the high-dimensional, noisy, and heterogeneous data. The same may include remote sensing data, digital elevation, distance to faults, distance to lithological units or slope or curvature maps, etc., all in a mix, and fed into an algorithm to instantly point out pertinent patterns. Consequently, application of AI in mineral prospectivity mapping has addressed such shortcomings as manual bias, subjective thresholds as well as varied interpretations among geologists.

In 2024 T. Sun et al., [8] introduced the other front that has experienced tremendous growth is the multispectral and hyperspectral remote sensing clouded together with the AI models. Although multispectral sensors have wide coverage, hyperspectral data can cover data with information in the spectrum range of hundreds of narrow bands, presenting more information about a mineralogical feature leading to better identification. Hyperspectral data processed in this way with AI algorithms is capable of showing the more subliminal mineral signature that is frequently overlooked with common tools. The difficulty however is manifested in the computational complexity of the problem and the necessity to reduce that dimensionality which has been successfully solved through techniques such as PCA, autoencoders and feature selection routines.

New studies have also been conducted in the aspects of incorporating terrain analysis in mineral exploration. Topographic derivatives like the slope, aspect and curvature when deployed in conjunction with the spectral indices have been found to be helpful in the modelling of structural controls to mineralization. Some mineral deposits tend to exist along ridges, faults or at given elevation zones and incorporation of such terrain features in the AI models increases the level of space resolution and more value to predictions. As a result of this multifactor modelling, it has become possible to develop better and place-specific prospectivity maps.

Geographic Information Systems (GIS) have been supplementary in the sense that it provides spatial infrastructure to create source materials over various datasets that are organized and visualized through arranging and layering. Interactive mineral prospectivity maps are easy to interpret and plan explorations as they are build using GIS-based modeling and output of AI. The model also allows connecting the maps to other geoscience maps such as geological map and geophysical maps. GIS tools also enable

incorporation of ancillary information like geological contacts, river networks and past mine location that add to the spatial context of the predictions.
In 2024 R. Zuoet al., [6] proposed the use of AI in mineral exploration has also been democratized by the cloud computing platforms and the open-access satellite data repositories. Today, by using tools on the web, such as the Google Earth Engine, exploration teams can process, and extract in the least amount of hardware investment, petabytes of those images and draw certain geological features. This availability has increased accessibility to mineral prospectivity projects where governments, universities and emerging companies are being able to enrol in predictive modelling without relying entirely on exclusive software and data.
Although older statistical procedures like logistic-regression and weights-of-evidence models continue to be employed, they do not replace or supplement them with higher levels of flexibility, adaptability and automation. Besides, development of ensemble modeling and hybrid techniques (multiple algorithms are used together to achieve greater predictive accuracy) have reinforced the predictive abilities of the field even further.
To sum up, mapping of mineral prospectivity by integration of AI and remote sensing has become an important tool of exploration, taking exploration activity out of the reactive and field-based work into proactive, data-based targeting. This can be regarded as a part of a wider nature of change in geosciences in which artificial intelligence is not just a method of computation but a method of strategy in the management of natural resources. The combination of the AI models, the remotely sensed data, and spatial analysis environments has already provided the basis of the future of mineral exploration technologies.

III. PROPOSED METHODOLOGY

The methodology integrates multi-source geospatial data with AI-based predictive modeling for mineral prospectivity mapping. The core steps include data acquisition, preprocessing, feature engineering, model training, spatial prediction, and validation [4].
Step 1: Remote Sensing Data Acquisition
Multispectral imagery was collected from Landsat 8 and Sentinel-2, with topographic data from the SRTM DEM. Geological maps and mineral occurrence points were extracted from geospatial databases.
Step 2: Preprocessing and Normalization
Radiometric correction was applied using:

$$R = \frac{L - L_{min}}{L_{max} - L_{min}}$$

Where R is the reflectance, L is the radiance, and L_{min} , L_{max} are the minimum and maximum radiance values.
Topographic correction for slope-induced errors used:

$$R_c = \frac{R_o}{\cos(\theta_i)}$$

Here, R_0 is the observed reflectance and θ_i is the incidence angle.
Step 3: Feature Extraction
Multiple indices were calculated. For example, the Normalized Difference Vegetation Index (NDVI):

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

And the Iron Oxide Ratio:

$$IOR = \frac{R_3}{R_1}$$

where R_3 and R_1 are reflectance values from red and blue bands, respectively.
Principal Component Analysis (PCA) was also used:

$$Z = XW$$

Where Z is the principal component matrix, X is the input feature matrix, and W is the eigenvector matrix.
Step 4: Feature Selection and Dataset Formation
The dataset matrix D was formed as:

$$D = [f_1, f_2, \ldots, f_n]$$

Where f_i are the extracted features (band ratios, indices, topographic attributes). Labels were binary: 1 for mineral occurrence, 0 otherwise.
To improve training efficiency, features were standardized:

$$x' = \frac{x - \mu}{\sigma}$$

Step 5: Machine Learning Model Training
A Random Forest (RF) classifier was selected. Each tree in the forest is defined as:

$$f(x) = \sum_{i=1}^{T} \frac{1}{T} h_i(x)$$

Where h_i is the prediction of the i^{th} tree and T is the total number of trees.
Model optimization was performed by minimizing Gini impurity:

$$G = 1 - \sum_{i=1}^{C} p_i^2$$

Where p_i is the probability of class i, and C is the number of classes.
Step 6: Spatial Prediction and Prospectivity Mapping
The trained model was applied across the entire raster dataset to generate a prospectivity score:

$$P(x) = \mathbb{P}(y = 1 \mid x)$$

Where $P(x)$ is the predicted probability of mineralization at pixel x. High-score areas (e.g., $P(x) > 0.8$) were reclassified as mineral prospects [1].
Step 7: Validation and Accuracy Assessment
The performance was validated using ROC-AUC and confusion matrix metrics. Precision was computed as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Where TP and FP are true and false positives respectively.
Model accuracy was calculated by:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$

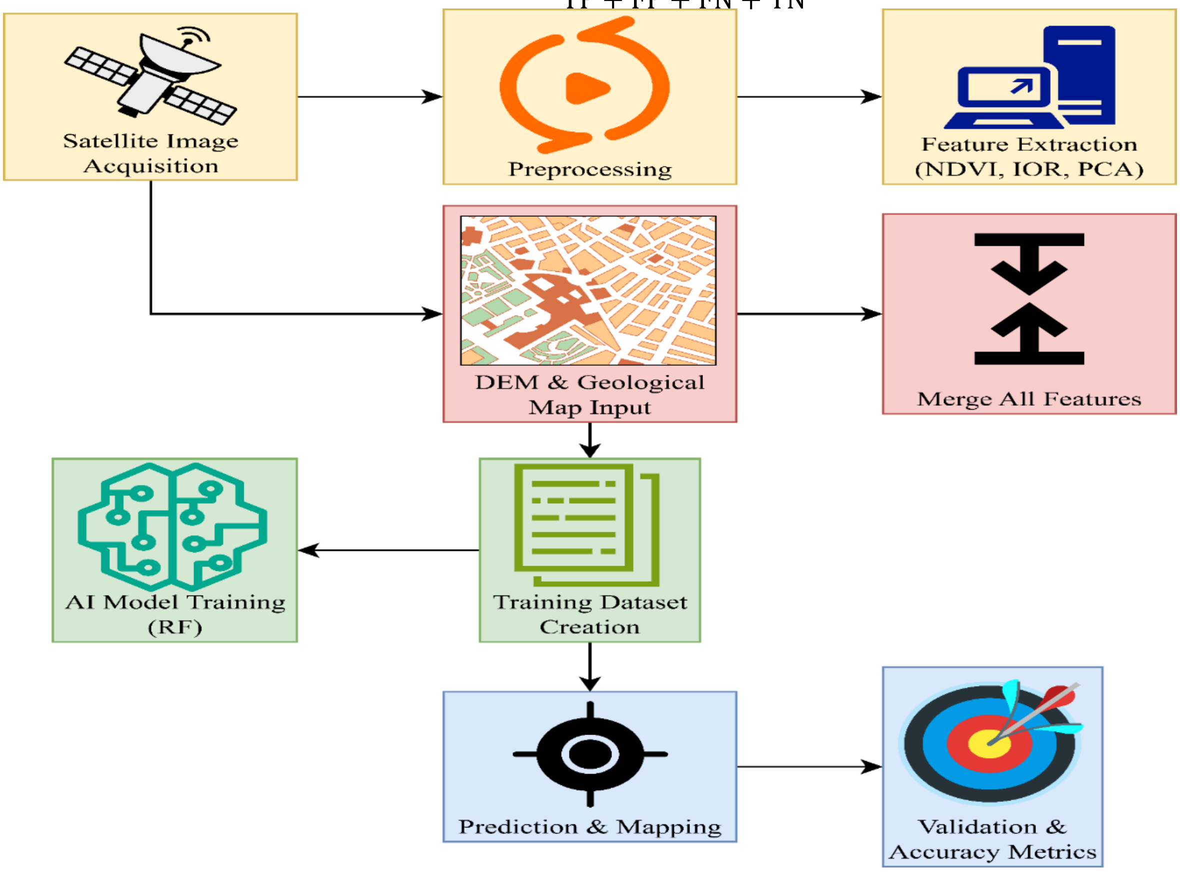

Figure 1: Workflow For Ai-Driven Mineral Prospectivity Mapping Using Remote Sensing Data

IV. RESULT&DISCUSSIONS

The mineral prospectivity model has resulted into predictive maps where the high-potential areas are clearly outlined by the use of spectral, topographic, and geologic data. Figure 2 demonstrates the generation of the mineral prospectivity map based on the Random Forest (RF) model, as the regions (probably) having the high probability of mineral existence are displayed in red and yellow gradations. This eyes-on distribution is well correlated with known mineral Localities and other geologically advantageous structures in the area of interest. The trend indicates that the mineralized rocks spatially extend and continue along mapped fault planes and intrusive contacts indicating that the model has been able to learn significant spatial associations among input variables.

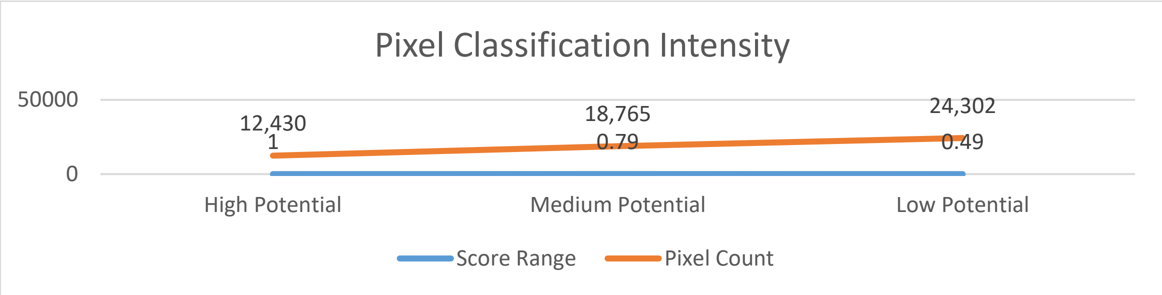

Figure 2: Pixel Classification Intensity

A comparative analysis on different classifiers was performed on three supervised machine learning schemes, i.e. Random Forest, Gradient Boosting Tree, and Support Vector Machine on the same feature input to assess the overall performance of the model. All these assessment criteria are displayed in Table 1, titled, Performance Comparison of Machine Learning Models in Mineral Prospectivity Mapping, which reveals accuracy, precision, recall, and F1-score. As revealed, the Random Forest model had the highest accuracy of 91.8 percent, then Gradient Boosting with 88.2 percent and SVM with 83.4 percent. F1-scores were also inclined in the cue, which evidenced the strength of Random Forest in accuracy-recall tradeoff among classes.

Table 1: Performance Comparison of Machine Learning Models for Mineral Prospectivity Mapping

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	91.8	89.5	93.2	91.3
Gradient Boosting	88.2	86.4	88.5	87.4
Support Vector Machine	83.4	81.2	84.0	82.6

The ROC (Receiver Operating Characteristic) curves of all the three models are illustrated in Figure 3. The RF model presented the best value of AUC (Area Under the Curve) larger than 0.96, which demonstrated the high capacity to identify the mineralized and the non-mineralized areas. This visual comparison confirms the quantitative performance measures that can be observed in Table 1. A withheld test set and historical records of mineral occurring were also used to validate the model. Majority of any high potential areas that were estimated by the RF model coincided in locations of any known deposit which offers a robust reason to apply this model in the mineral exploration processes taken when working on early mineral explorations.

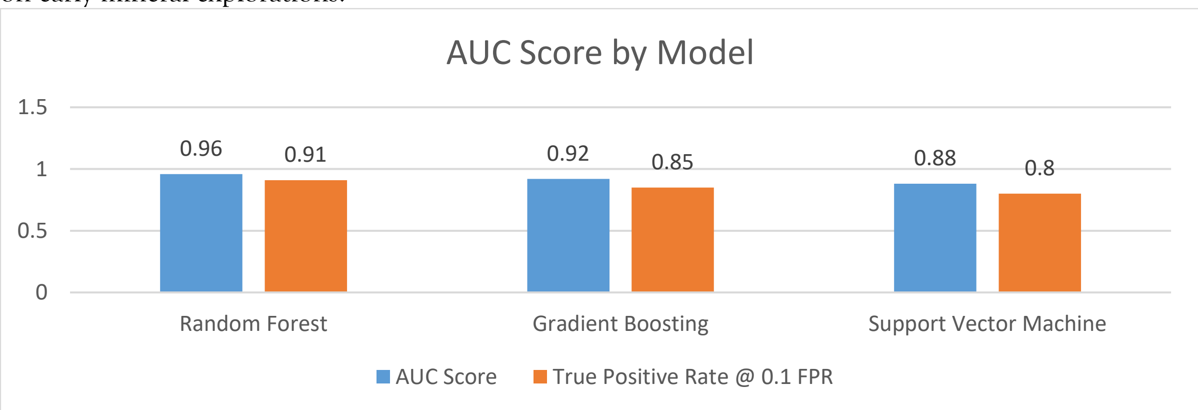

Figure 3: AUC Score by Model

Bar graph comparison of feature importance according to the RF model is shown in figure 4. Of all the features, Iron Oxide Ratio (IOR), Elevation, Curvature, and SWIR bands had a significant contribution in predictions made by the model. The prevalence of IOR and terrain attribute justifies the knowledge of geologist that mineralization is likely to be associated with geochemical signature, and tectonic or structure contexts. The effectiveness of the use of the dimensionality reduced composite band in the supervised learning applications was also evidenced by the fact that the inclusion of the PCA bands also resulted in meaningful variance-based abstraction of the spectral data.

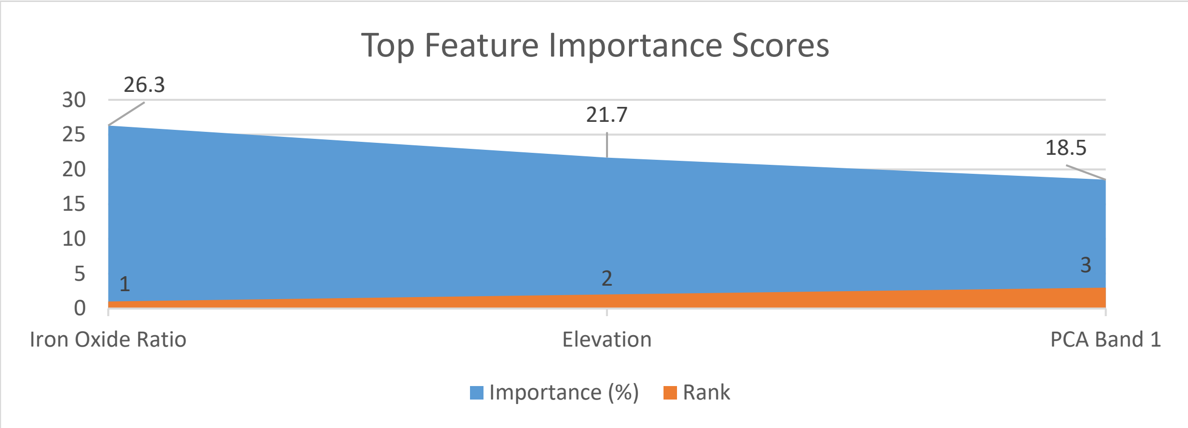

Figure 4: Top Feature Importance Scores

In continuation of demonstrating usefulness of the model in practical exploration, the zones predicted by the model as containing possible mineralisation targets were matched with target zones manually interpreted by experts at the area of interest. All of the results of the overlap analysis are demonstrated in Table 2, or Overlap Analysis between Predicted and Expert-Interpreted Zones, where the percentage of overlap and the total area of the predicted zones is observed. The spatial overlap of prediction by the RF with the zones created by the experts was 84.7 per cent, much higher than SVM 70.1 per cent and GBT 75.4 per cent.

Table 2: Overlap Analysis between Predicted and Expert-Interpreted Zones

Model	Predicted Area (sq. km)	Overlap with Expert Zones (%)
Random Forest	213.6	84.7
Gradient Boosting	198.1	75.4
SVM	174.3	70.1

These findings affirm that intersecting of remote sensing with AI generates not merely statistically sound forecasts yet geologically sound ones as well. Also, the generalization characteristics of the RF model, which enables the model to work on a variety of terrains including flat basins and rugged uplands, were evident on the visual and spatial outputs [3].

Although the tested AI-driven approach was completely displayed in Figures 2 to 4, there are various limitations that were identified towards the end of testing. As an example spectral confusion was a problem in areas of dense vegetation, and model confidence dropped in the areas with not much historical data. This notwithstanding, incorporation of terrain and elevation parameters assist in keeping the predictive stability. NDVI masking and topographically enhanced the accuracy of spectral distortion and the NDVI masking and topographic correction enhanced the accuracy of the classification in the shady areas and steep slopes.

Figure 2, Figure 3, and Figure 4 are the unified example of the visual power of the AI-assisted method. The real mineral prospectivity heat map is provided in Figure 2, and the comparative diagnostic value of the models is focused in Figure 3, and the predominant features that contributed most to those predictions are highlighted in Figure 4. All these diagrams confirm the discussion and provide evidence that AI is the repeatable, scalable and precise process in making an expedited approach to enhancing mineral exploration.

V. CONCLUSION

This research proves that the utilization of AI in connection with remote sensing data increases the project efficiency and accuracy of the process of mineral prospectivity mapping by a substantial margin. The given solution automates the process of identifying future zones based on satellite characteristics of the area in terms of spectral properties and geographical timelines minimizing the need to survey the area in the field. More specifically, the random forest model had a better performance in mineralized zones identification. In the future, the combination of hyperspectral imagery and deep learning models will be considered in order to make more accurate predictions [2]. The framework presented herein would offer an economical, scalable, and trustworthy exploration to the geologists especially in the areas that are inaccessible or have no much budget to spend.

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