International Journal of Science Academic Research
Vol. 07, Issue 09, pp.1388-1397, September 2026
Available online at http://www.scienceijsar.com

ISSN: 2582-6425

Research Article

APPLICATION OF MULTISPECTRAL SATELLITE IMAGERY AND ARTIFICIAL INTELLIGENCE-BASED MACHINE LEARNING FOR MINERAL EXPLORATION: A CASE STUDY OF KOSSANTO, WESTERN MALI

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Received 18th July 2026; **Accepted** 26th August 2026; **Published online** 11th September 2026

Abstract

The discovery of new gold deposits increasingly requires innovative exploration methods capable of integrating complex geoscientific datasets. This study presents an integrated approach combining multispectral satellite imagery, Geographic Information Systems (GIS), and artificial intelligence (AI)-based machine learning for predictive mineral prospectivity mapping in the Kossanto area, western Mali. The datasets used include Sentinel-2 MSI and Landsat 8 OLI imagery, together with geological, structural, and topographic data. Several remote sensing techniques, including false-color composites, spectral band ratios, Principal Component Analysis (PCA), and hydrothermal alteration indices, were applied to extract spectral signatures associated with lithological units and mineralized zones. The derived variables were subsequently integrated into three machine learning models: Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN). The results demonstrate the ability of these models to capture complex relationships between spectral, geological, and structural parameters for predicting gold mineralization. Among the evaluated algorithms, the CNN model achieved the highest predictive performance, followed by Random Forest and SVM, confirming the effectiveness of machine learning techniques in mineral prospectivity mapping. The resulting prospectivity map highlights priority exploration targets closely associated with major tectonic structures, lithological contacts, and hydrothermal alteration zones. The findings demonstrate that integrating multispectral remote sensing with artificial intelligence provides a robust and cost-effective framework for optimizing gold exploration, reducing exploration costs, and improving target selection within the West African Craton.

Keywords: Multispectral remote sensing, Machine learning, Gold exploration, Mineral prospectivity mapping, Kossanto, West African Craton.

INTRODUCTION

The discovery of new mineral deposits has become a major strategic challenge in response to the rapidly growing global demand for critical and precious metals, driven by the energy transition, digital technologies, and industrial development (Ali *et al.,* 2017; Hund *et al.,* 2020). However, conventional mineral exploration methods are often constrained by high operational costs, lengthy implementation times, and limited accessibility to remote or geologically complex terrains (Bonham-Carter, 1994; Carranza, 2008). These limitations have encouraged the development of innovative geospatial technologies capable of improving the efficiency and accuracy of mineral exploration. Remote sensing, Geographic Information Systems (GIS), and artificial intelligence (AI) have emerged as powerful tools for mineral prospectivity mapping and exploration targeting (Van der Meer *et al.,* 2012). Multispectral satellite sensors such as Landsat, Sentinel-2, and ASTER provide valuable information for identifying lithological units, hydrothermal alteration zones, structural lineaments, and other geological features associated with mineralization (Sabins, 1999; Pour & Hashim, 2015; Cracknell & Reading, 2014). The integration of remotely sensed information with geological, geophysical, and geochemical datasets significantly enhances the understanding of mineralizing systems and improves the delineation of prospective exploration targets (Carranza, 2008).

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In recent years, Machine Learning (ML) has revolutionized geoscientific data analysis by enabling the identification of complex nonlinear relationships among geological, geophysical, geochemical, and spectral variables (Jordan & Mitchell, 2015; Maxwell *et al.,* 2018; Dramsch, 2020). Machine learning algorithms have demonstrated remarkable predictive capabilities in mineral prospectivity mapping, reducing subjectivity while improving exploration efficiency. Among the most widely applied algorithms are Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN), which have achieved high predictive accuracies in numerous mineral exploration studies (Breiman, 2001; Cortes & Vapnik, 1995; Mountrakis *et al.,* 2011). Their ability to process large and heterogeneous geoscientific datasets makes them particularly suitable for modern exploration workflows. Mali is located within the West African Craton, one of the world's most productive Paleoproterozoic gold provinces, hosting several world-class gold deposits such as Kéniéba, Loulo-Gounkoto, Sadiola, Fekola, and Kossanto (Milési *et al.,* 1992; Feybesse *et al.,* 2006; Lawrence *et al.,* 2013). Despite its considerable mineral endowment, several areas remain underexplored because of their complex geological setting, limited accessibility, and insufficient integration of modern exploration techniques. The Kossanto area, characterized by Birimian volcano-sedimentary formations, granitoid intrusions, extensive fault systems, and hydrothermal alteration, represents an excellent case study for applying advanced remote sensing and artificial intelligence approaches to gold exploration (Carranza, 2008).This study proposes an integrated methodology combining multispectral satellite imagery, Geographic Information Systems (GIS), and Machine Learning techniques to identify areas favorable for gold mineralization in the Kossanto region of western Mali. Specifically, the study aims to (i) extract spectral, lithological, and structural information from Sentinel-2 MSI and Landsat 8 OLI imagery; (ii) integrate these variables with geological and topographic datasets within a GIS environment; (iii) compare the predictive performance of Random Forest, Support Vector Machine, and Convolutional Neural Network models; (iv) generate a mineral prospectivity map highlighting priority exploration targets; and (v) evaluate model performance using quantitative metrics including Overall Accuracy (OA), Cohen's Kappa coefficient, Receiver Operating Characteristic–Area Under the Curve (ROC-AUC), precision, recall, F1-score, and confusion matrices (Yesilnacar *et al.,* 2020; Chen *et al.,* 2020; Maxwell *et al.,* 2018). The results are expected to demonstrate that integrating multispectral remote sensing with artificial intelligence provides a robust, efficient, and cost-effective framework for mineral prospectivity mapping. Furthermore, the proposed approach offers valuable decision-support tools for reducing exploration risk, optimizing field investigations, and improving mineral target selection within the West African Craton, thereby contributing to the sustainable development of mineral resources in Mali and comparable geological environments.

MATERIALS AND METHODS

Geological Setting of the Study Area

The Kossanto study area is located in western Mali within the Paleoproterozoic West African Craton (WAC), specifically in the eastern part of the Kéniéba-Kayes Inlier, one of the most important gold-producing regions in West Africa. This geological province belongs to the Birimian Greenstone Belt, which developed between approximately 2.25 and 2.0 Ga and consists of metamorphosed volcano-sedimentary sequences intruded by granitoid complexes and affected by multiple episodes of tectonic deformation (Milési *et al.,* 1992; Feybesse *et al.,* 2006; de Kock *et al.,* 2012). Lithologically, the Kossanto area is dominated by Birimian formations composed of mafic to intermediate volcanic rocks, including basalts, andesites, and volcaniclastic deposits, interlayered with volcano-sedimentary successions consisting of greywackes, schists, pelitic rocks, and banded iron formations (BIFs). These units are intruded by granitoid and granodioritic bodies that played a fundamental role in the regional geodynamic evolution, crustal differentiation, and the formation of gold mineralization (Feybesse *et al.,* 2006; Oberthür *et al.,* 1998). The Birimian terranes of the West African Craton constitute one of the world's principal geological environments for orogenic gold deposits, hosting numerous economically significant gold camps (Goldfarb *et al.,* 2005).Structurally, the region is characterized by a complex network of faults, fractures, and ductile shear zones predominantly oriented NE–SW to N–S, reflecting the polyphase tectonic evolution of the Birimian orogen. These tectonic structures acted as preferential pathways for hydrothermal fluid circulation and exert a primary control on the spatial distribution of gold mineralization. Gold occurrences are commonly associated with lithological contacts, major shear corridors, and highly fractured zones affected by intense hydrothermal alteration dominated by quartz, carbonates, sulfides, and iron oxides (Lawrence *et al.,* 2013; Robert *et al.,* 2007). The metallogeny of Kossanto conforms to the classical model of Birimian orogenic gold deposits, where mineralization is closely related to crustal-scale deformation, hydrothermal fluid flow, and extensive wall-rock alteration (Goldfarb *et al.,* 2005; Groves *et al.,* 2003). The principal hydrothermal alteration assemblages include silicification, carbonatization, sericitization, chloritization, and oxidation of sulfide minerals. These alteration minerals produce distinctive spectral signatures that can be effectively detected using multispectral satellite imagery, making them valuable exploration indicators for modern mineral prospecting (Sabins, 1999; Pour & Hashim, 2015). From an exploration perspective, the geological complexity of the Kossanto area presents significant challenges for conventional field-based exploration methods but also offers an ideal environment for the application of integrated geospatial technologies. The combination of multispectral remote sensing, Geographic Information Systems (GIS), and Machine Learning (ML) enables the simultaneous analysis of spectral information related to alteration minerals, geological formations, structural features, and topographic parameters. Such integration enhances mineral prospectivity mapping by identifying spatial relationships among exploration variables that are difficult to recognize using traditional methods alone (Carranza, 2008; Van der Meer *et al.,* 2012).A comprehensive understanding of the geological and structural framework of Kossanto therefore constitutes a fundamental prerequisite for developing reliable artificial intelligence-based predictive models. Integrating geological observations with multispectral satellite data provides valuable insights into the spatial controls of gold mineralization and significantly improves the identification and prioritization of exploration targets within the Birimian terranes of western Mali. This integrated approach contributes to reducing exploration uncertainty while supporting more efficient and cost-effective mineral exploration strategies.

Study Period and Data Acquisition Strategy

The study was conducted in the Kossanto region, located in western Mali within the Kéniéba-Kayes Inlier of the Paleoproterozoic West African Craton. The research was carried out over a period encompassing all major stages of the investigation, including literature review, satellite data acquisition and preprocessing, field investigations, spatial database development, and machine learning-based mineral prospectivity modeling. This workflow ensured the systematic integration of multisource geoscientific datasets required for predictive mineral exploration. A comprehensive data acquisition strategy was designed to collect geological, structural, topographic, and mineralogical information controlling gold mineralization. Field campaigns involved systematic geological mapping aimed at identifying the principal lithological units, structural features including faults, fractures, and shear zones and hydrothermal alteration associated with gold-bearing systems. Particular emphasis was placed on the characterization of Birimian volcano-sedimentary formations, granitoid intrusions, and lithological contacts that may have influenced hydrothermal fluid circulation and ore deposition. Special attention was devoted to recognizing hydrothermal alteration assemblages commonly associated with orogenic gold deposits, including silicification, sericitization, carbonatization, chloritization, and sulfide oxidation. These alteration types constitute key exploration indicators because they generate distinctive spectral responses that can be detected using multispectral satellite imagery. Field observations were recorded using high-precision Global

Positioning System (GPS) receivers to ensure accurate georeferencing of geological outcrops, structural measurements, alteration zones, and mineral occurrences. These georeferenced observations were subsequently used as reference data for validating remote sensing products and training the machine learning algorithms. Complementary remote sensing datasets consisted primarily of Sentinel-2 Multi Spectral Instrument (MSI) and Landsat 8 Operational Land Imager (OLI) imagery. These satellite datasets were selected because of their suitable spatial, spectral, and temporal resolutions for lithological discrimination and hydrothermal alteration mapping. Prior to analysis, the images underwent standard preprocessing procedures, including radiometric calibration, atmospheric correction, geometric correction, cloud masking, and image mosaicking where necessary. Advanced image processing techniques were then applied, including false-color composite generation, spectral band ratio analysis, Principal Component Analysis (PCA), and hydrothermal alteration indices to enhance the discrimination of lithological units and alteration minerals associated with gold mineralization. All geological field observations and remotely sensed products were integrated within a Geographic Information System (GIS) to establish a comprehensive geospatial database. The database included geological maps, structural lineaments, lithological boundaries, topographic variables derived from digital elevation models (DEMs), spectral alteration layers, and validated mineral occurrence locations. These datasets were standardized and converted into raster predictor variables suitable for machine learning analysis.The field observations and known mineral occurrences served as ground-truth data for training, validating, and testing the predictive performance of the machine learning algorithms. Training samples representing mineralized and non-mineralized locations were extracted from the integrated GIS database and used to develop mineral prospectivity models based on Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN) algorithms. Independent validation datasets were employed to assess model robustness using statistical performance metrics. Overall, the adopted data acquisition strategy relied on a multidisciplinary framework integrating field geology, multispectral remote sensing, GIS-based spatial analysis, and artificial intelligence. This integrated methodology provides a reliable basis for understanding the geological controls on gold mineralization in the Kossanto area while significantly improving predictive mineral prospectivity mapping and exploration target selection within the Birimian terranes of western Mali.

Data used in this study

This study is based on the integration of multiple geoscientific datasets to develop a predictive mineral prospectivity mapping framework combining multispectral remote sensing, Geographic Information Systems (GIS), and Machine Learning (ML). The integrated database includes satellite imagery, geological and structural information, topographic data, and reference datasets used for training and validating the artificial intelligence models. Combining these complementary data sources enables the identification of spatial relationships between geological features and gold mineralization, thereby improving the accuracy and reliability of mineral prospectivity prediction.

Multispectral Satellite Data: Multispectral satellite imagery constituted the primary source of spatial information used in this study. The datasets were acquired from the Sentinel-2 MultiSpectral Instrument (MSI) and the Landsat 8 Operational Land Imager (OLI), selected because of their spectral capabilities, spatial resolution, and suitability for geological mapping and hydrothermal alteration detection. The Sentinel-2 MSI imagery provides spatial resolutions of 10 m, 20 m, and 60 m across thirteen spectral bands covering the visible (VIS), near-infrared (NIR), red-edge, and shortwave infrared (SWIR) regions of the electromagnetic spectrum. The inclusion of red-edge and SWIR bands makes Sentinel-2 particularly effective for discriminating litho logical units and identifying hydrothermal alteration minerals such as iron oxides, clay minerals, hydroxyl-bearing minerals, and carbonate-rich alteration assemblages. These spectral characteristics significantly enhance the detection of mineralogical variations associated with gold-bearing hydrothermal systems. The Landsat 8 OLI imagery was incorporated because of its long-term temporal continuity, global coverage, and well-established applications in mineral exploration. Its spectral bands are particularly suitable for mapping iron oxide minerals, clay-rich alteration zones, hydroxyl-bearing minerals, and lithological contacts. Furthermore, the extensive Landsat archive provides consistent observations that facilitate regional geological interpretation and comparison with previous exploration studies. Prior to analysis, all satellite images underwent standard preprocessing procedures to improve data quality and ensure consistency between datasets. These preprocessing steps included radiometric calibration, atmospheric correction, geometric correction, cloud and shadow masking, and image co-registration. Following preprocessing, several advanced remote sensing techniques were applied to enhance the discrimination of geological and alteration features, including:

- False-color composite (FCC) generation;
- Spectral band ratio analysis;
- Principal Component Analysis (PCA);
- Hydrothermal alteration spectral indices;
- Image enhancement techniques for lithological and structural mapping.

These image processing methods enhanced spectral contrasts between lithological units and alteration minerals, allowing the extraction of predictor variables subsequently integrated into the GIS database and used as input features for the Machine Learning models. The processed multispectral datasets therefore constitute the fundamental geospatial information source for detecting geological structures, alteration zones, and other exploration indicators associated with gold mineralization in the Kossanto area.

Geological and Lithological Data: The geological dataset comprised information on lithological formations, geological units, and petrographic characteristics of the Kossanto region. These data were compiled from existing geological maps, published literature, exploration reports, and field investigations conducted during this study. The dataset enabled the identification and mapping of the principal geological formations within the study area, including Birimian volcano-sedimentary sequences, mafic to intermediate volcanic rocks, metamorphosed sedimentary formations, and granitoid intrusions. Lithological information constitutes one of the most important predictor variables in mineral prospectivity mapping because different rock types exhibit distinct spectral signatures and varying degrees of favorability for gold mineralization.

The geological database was therefore integrated with the remotely sensed products to improve lithological discrimination and to generate reliable training datasets for the machine learning models.

Structural and Tectonic Data: Structural information plays a fundamental role in controlling the localization of orogenic gold mineralization. The structural dataset used in this study includes faults, fractures, shear zones, fold axes, and lithological contacts derived from geological maps, field observations, and satellite image interpretation. Structural lineaments were extracted using both manual interpretation and image enhancement techniques applied to Sentinel-2 and Landsat 8 imagery. These structural features were subsequently integrated into the GIS database as predictor variables because major tectonic structures frequently act as conduits for hydrothermal fluid circulation and ore deposition. The inclusion of structural variables allowed the machine learning models to quantify the spatial influence of tectonic controls on gold mineralization and improve mineral prospectivity prediction.

Digital Elevation Model (DEM): A Digital Elevation Model (DEM) was incorporated to characterize the geomorphological properties of the study area. The DEM provided topographic variables that may influence geological processes, weathering intensity, erosion patterns, and the exposure of mineralized rocks.From the DEM, several terrain derivatives were generated, including:

- Elevation;
- Slope;
- Aspect;
- Curvature;
- Hillshade;
- Terrain ruggedness and morphostructural features.

These topographic variables complement the geological and spectral datasets by providing additional information on geomorphological controls associated with hydrothermal alteration and mineralization. Moreover, terrain analysis facilitates the identification of structural discontinuities and erosional windows that may expose mineralized zones.

Training and Validation Datasets: The machine learning models were developed using carefully prepared training and validation datasets derived from field observations, known mineral occurrences, geological mapping, and remotely sensed information. Reference samples were selected from confirmed mineralized locations and representative non-mineralized areas exhibiting contrasting geological and spectral characteristics. The compiled dataset was randomly partitioned into training (70%) and validation/testing (30%) subsets to ensure an objective evaluation of model performance. The predictor variables extracted from satellite imagery, geological maps, structural layers, and DEM-derived products were combined to form the input feature space for the machine learning algorithms.

Three supervised machine learning approaches were evaluated:

- Random Forest (RF);
- Support Vector Machine (SVM);
- Convolutional Neural Network (CNN).

Model performance was quantitatively assessed using several statistical indicators, including:

- Overall Accuracy (OA);
- Cohen's Kappa coefficient;
- Precision;
- Recall;
- F1-score;
- Receiver Operating Characteristic–Area Under the Curve (ROC-AUC);
- Confusion Matrix;
- Root Mean Square Error (RMSE), where applicable.

These evaluation metrics enabled a comprehensive comparison of predictive performance and generalization capability among the different algorithms. Overall, the integrated geoscientific database combines spectral, geological, structural, and topographic information, providing a robust foundation for artificial intelligence-based mineral prospectivity mapping and significantly enhancing the identification of favorable gold exploration targets in the Kossanto region.

Software and Analytical Tools

This study employed a combination of field equipment, geospatial software, programming environments, and machine learning frameworks to support the acquisition, processing, analysis, visualization, and interpretation of geoscientific data. The adopted workflow integrates multispectral remote sensing, Geographic Information Systems (GIS), and artificial intelligence (AI) to improve mineral prospectivity mapping in the Kossanto area. Field investigations were carried out using Global Positioning System(GPS) receivers for accurate georeferencing of geological observations, a geological compass for measuring structural orientations (strike and dip), and a digital camera for documenting lithological units, hydrothermal alteration, and mineral occurrences. These field data provided the ground-truth information required for model calibration and validation. Multispectral satellite imagery from Sentinel-2 MSI and Landsat 8 OLI was processed using ENVI 5.6, where radiometric and atmospheric corrections, image enhancement, false-color composites, spectral band ratios, Principal Component Analysis (PCA), and hydrothermal alteration indices were generated. These processing techniques enhanced lithological discrimination and facilitated the identification of alteration minerals associated with gold mineralization. Spatial analysis and cartographic production were performed using ArcGIS Pro and QGIS. These GIS platforms were employed for geodatabase management, thematic layer integration, spatial analysis, multicriteria evaluation, raster processing, lineament extraction, and the production of geological, structural, and mineral prospectivity maps.

Machine learning analyses were implemented in the Python programming language using the Jupyter Notebook environment. Data preprocessing and feature engineering were conducted with the NumPy and Pandas libraries, while supervised classification models including Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting were developed using Scikit-learn. Deep learning models, particularly Convolutional Neural Networks (CNNs), were implemented using Tensor Flow and Keras, enabling the automated extraction of complex spatial and spectral patterns associated with gold mineralization. Statistical analyses and model validation were performed using both Python and R. Model performance was evaluated through Overall Accuracy (OA), Cohen's Kappa coefficient, Precision, Recall, F1-score, ROC-AUC, confusion matrices, and Root Mean Square Error (RMSE). These complementary metrics ensured a comprehensive assessment of predictive capability, classification reliability, and model robustness. Scientific figures, charts, tables, and graphical illustrations were prepared using Microsoft Excel, Microsoft PowerPoint, and Adobe Illustrator, facilitating the presentation of quantitative results and geological interpretations in publication-quality formats. Collectively, these tools established an integrated analytical workflow extending from field data acquisition and satellite image processing to GIS-based spatial analysis and artificial intelligence-driven predictive modeling. This multidisciplinary framework significantly enhanced the identification and prioritization of gold exploration targets in the Kossanto region while providing a reproducible methodology applicable to other Birimian terrains within the West African Craton.

METHODOLOGY

The methodology adopted in this study is based on an integrated framework combining field geology, multispectral remote sensing, Geographic Information Systems (GIS), and Machine Learning (ML) techniques to identify and map areas favorable for gold mineralization in the Kossanto region of western Mali. This multidisciplinary approach enables the integration of heterogeneous geoscientific datasets and improves the predictive capability of mineral exploration models by exploiting the complementary strengths of geological knowledge, spatial analysis, and artificial intelligence (Bonham-Carter, 1994; Carranza, 2008).The overall methodological workflow consisted of two major phases. The first phase involved the acquisition, preprocessing, and integration of geoscientific datasets, including satellite imagery, geological maps, structural information, and field observations. The second phase focused on spatial analysis, feature extraction, machine learning model development, validation, and mineral prospectivity mapping.

Acquisition, Processing, and Integration of Geoscientific Data

The first stage of the methodology consisted of compiling and preprocessing all available geoscientific information relevant to the study area. Existing geological maps, structural datasets, published exploration reports, mineral occurrence records, and multispectral satellite imagery were collected and standardized within a common spatial reference framework. These datasets provided the geological context necessary to identify the principal factors controlling gold mineralization within the Birimian terranes of the West African Craton (Milési *et al.,* 1992; Feybesse *et al.,* 2006).Field investigations represented a critical component of the study by providing reliable ground-truth information for both image interpretation and machine learning model validation. Geological surveys focused on describing lithological units, identifying tectonic structures including faults, fractures, and shear zones and mapping hydrothermal alteration zones associated with gold mineralization. All field observations were accurately georeferenced using Global Positioning System (GPS) receivers, ensuring the development of a high-quality spatial database suitable for subsequent GIS analysis and predictive modeling (Lawrence *et al.,* 2013).Remote sensing analysis was performed using Sentinel-2 MultiSpectral Instrument (MSI) and Landsat 8 Operational Land Imager (OLI) imagery. Before analysis, all satellite datasets underwent standard preprocessing procedures, including radiometric calibration, atmospheric correction, geometric correction, image co-registration, cloud masking, and contrast enhancement. These preprocessing operations ensured radiometric consistency and improved the quality of the derived spectral information. Several image enhancement techniques were subsequently applied to maximize lithological discrimination and hydrothermal alteration detection. These included false-color composite generation, spectral band ratio analysis, Principal Component Analysis (PCA), and hydrothermal alteration mapping using diagnostic spectral indices. These techniques enhance spectral contrasts between geological units and facilitate the identification of alteration minerals such as iron oxides, clay minerals, hydroxyl-bearing minerals, and carbonate-rich assemblages that are commonly associated with orogenic gold systems (Sabins, 1999; Van der Meer *et al.,* 2012; Pour & Hashim, 2015).In addition to image enhancement, thematic layers representing lithology, structural lineaments, topography, hydrothermal alteration, and known mineral occurrences were generated and incorporated into a Geographic Information System (GIS). All predictor variables were harmonized to a common spatial resolution, projection, and raster format to ensure compatibility during machine learning analysis. The resulting multidimensional geospatial database provided a comprehensive representation of the geological environment and enabled quantitative analysis of the relationships between geological variables and the spatial distribution of gold mineralization. The integration of multispectral, geological, structural, and topographic information within the GIS environment significantly improved the characterization of exploration criteria and reduced uncertainties associated with individual datasets. This integrated spatial database formed the foundation for the subsequent machine learning models used to predict mineral prospectivity across the Kossanto region (Carranza, 2008).

Machine Learning Modeling and Performance Evaluation

The second methodological step consisted of applying Machine Learning algorithms to predict potential gold mineralization zones The input variables used in the models included satellite spectral bands, alteration indices, structural parameters, lithological data, and topographic information These variables were organized into training matrices designed to train and test the predictive models Several machine learning algorithms were applied, including Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting, and Convolutional Neural Networks (CNN) The Random Forest model, based on an ensemble of decision trees, presents a high generalization capacity and strong resistance to data noise (Breiman, 2001) The SVM model enables efficient class separation through the identification of optimal hyperplanes in multidimensional spaces (Cortes & Vapnik, 1995) Neural network models, particularly CNNs, are used due to their ability to automatically extract complex features from spatial and spectral datasets (Maxwell *et al.,* 2018; Dramsch, 2020)The databases were divided into training and validation datasets in order to evaluate the generalization capability of the models A k-fold cross-validation procedure was applied to reduce the risk of overfitting and improve the robustness of the results The performance of the models was evaluated using several statistical indicators, including Overall Accuracy, Cohen's Kappa coefficient, confusion matrix, Receiver Operating Characteristic (ROC) curve, Area Under the Curve (AUC), and Root Mean Square Error (RMSE)These indicators allow an objective comparison of the performance of the different algorithms and the identification of the most suitable model for mineral potential prediction (Fawcett, 2006) Finally, the results obtained from the Machine Learning models were integrated into a Geographic Information System (GIS) to produce a mineral prospectivity map of the Kossanto region This synthetic map enables the prioritization of areas with high gold potential and provides a decision-support tool to guide future mineral exploration campaigns.

SCIENTIFIC VALIDATION

Scientific validation represents a critical step in this study to assess the reliability of the results obtained through the integration of multispectral satellite data, geological information, and Machine Learning models. It aims to verify the ability of the developed approaches to reproduce the relationships between geological, structural, and spectral parameters associated with gold mineralization in the Kossanto area. The validation process is based on the comparison between the outputs of predictive models and reference datasets derived from field observations, known mineral occurrences, and available geoscientific information (Carranza, 2008; Maxwell *et al.,* 2018).

Validation Methods for Predictive Models

The validation of Machine Learning models was performed using a strategy combining the division of datasets into training and testing subsets, together with a k-fold cross-validation procedure. This approach allows the evaluation of the models' ability to generalize the learned relationships using independent datasets and reduces the risk of overfitting (Kohavi, 1995; Hastie *et al.,* 2009). The performance of the different algorithms used, particularly Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Networks (CNN), was compared using statistical indicators widely applied in remote sensing and predictive mapping studies. Overall Accuracy was used to evaluate the proportion of correctly classified samples, whereas the Kappa coefficient measured the level of agreement between model predictions and reference data while accounting for the agreement occurring by chance (Congalton & Green, 2009).The confusion matrix was also used to analyze the detailed performance of the models by identifying classification errors among the different mineral favorability classes. Parameters such as sensitivity, specificity, and error rate were used to assess the ability of the models to correctly identify areas favorable for gold mineralization (Fawcett, 2006). Model evaluation also included the analysis of Receiver Operating Characteristic (ROC) curves and the Area Under the Curve (AUC) to measure the discriminatory capability of the algorithms between mineralized and non-mineralized areas. A high AUC value indicates a better ability of the model to distinguish sectors with high gold potential from those with lower potential (Fawcett, 2006).

Geological and Cartographic Validation of Results

Geological validation consisted of comparing the mineral prospectivity maps generated by the models with field observations, major geological structures, and known gold occurrences in the Kossanto region. This step was performed to verify the geological consistency of the predictions and evaluate the relevance of the variables incorporated into the predictive models (Bonham-Carter, 1994).The areas identified as highly favorable were analyzed according to their relationship with the main geological controls of gold mineralization, including shear zones, lithological contacts, granitoid intrusions, and sectors affected by hydrothermal alteration. This comparison confirmed that the outputs generated by the artificial intelligence models are consistent with the fundamental metallogenic principles governing orogenic gold deposits within the West African Craton (Goldfarb *et al.,* 2005; Groves *et al.,* 2003).The agreement between the predicted high-potential zones and the known geological indicators provides additional evidence of the reliability and practical applicability of the developed models for mineral exploration targeting. The combination of statistical validation and geological validation ensures that the resulting prospectivity maps are both mathematically robust and geologically meaningful for identifying new gold exploration targets in the Kossanto region.

RESULTS

The results obtained in this study demonstrate the contribution of integrating multispectral satellite imagery, geological datasets, and Machine Learning algorithms for the identification of areas favorable to gold mineralization in the Kossanto region, western Mali. The analyses allowed the characterization of spectral signatures, lithological and structural controls, as well as the evaluation of the performance of the developed predictive models.

Analysis of Satellite Data and Mapping of Geological Parameters

The analysis of Sentinel-2 MSI and Landsat 8 OLI satellite imagery enabled the identification of several spectral signatures associated with lithological units and hydrothermal alteration zones. False-color composites, spectral band ratios, and Principal Component Analysis (PCA) improved the discrimination of geological formations, particularly Birimian volcanic rocks, volcano-sedimentary units, and granitoid intrusions. The calculated spectral indices highlighted areas enriched in iron oxides, clay minerals, and hydroxyl-bearing mineral phases, which are considered potential indicators of hydrothermal fluid circulation and gold mineralization. The most significant spectral anomalies were mainly located along lithological contacts and major structural corridors identified in the Kossanto region. The integration of satellite data with geological information enabled the development of a map of the main parameters controlling mineralization, emphasizing the importance of tectonic structures, particularly faults and shear zones oriented NE–SW to N–S. These structures appear to represent major controls on the spatial distribution of gold occurrences.

Machine Learning Modeling

The Machine Learning models developed in this study demonstrated a significant ability to identify relationships between spectral, geological, structural, and topographic variables associated with gold prospectivity. The Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN) algorithms were used to generate predictive mineral prospectivity maps. The Random Forest model showed good performance due to its ability to manage a large number of input variables and reduce the influence of noise within the datasets. The SVM model also produced satisfactory results by providing efficient separation between different mineral potential classes. The CNN model, based on deep learning approaches, demonstrated superior capability for automatically extracting complex spatial and spectral features from the integrated geoscientific datasets. The performance of the models was evaluated using statistical indicators. The results showed high overall accuracy values for the different algorithms, with a significant improvement in classification performance after integrating geological and structural information with spectral variables. The high values of the Kappa coefficient and AUC confirmed the robustness of the models for predicting areas favorable to gold mineralization. The comparison between the different algorithms revealed that the integration of multisource geoscientific data significantly enhanced predictive accuracy compared with the use of satellite spectral information alone. The Machine Learning models successfully captured the nonlinear relationships between geological controls and mineralization patterns, demonstrating their effectiveness as decision-support tools for gold exploration in the Kossanto region.

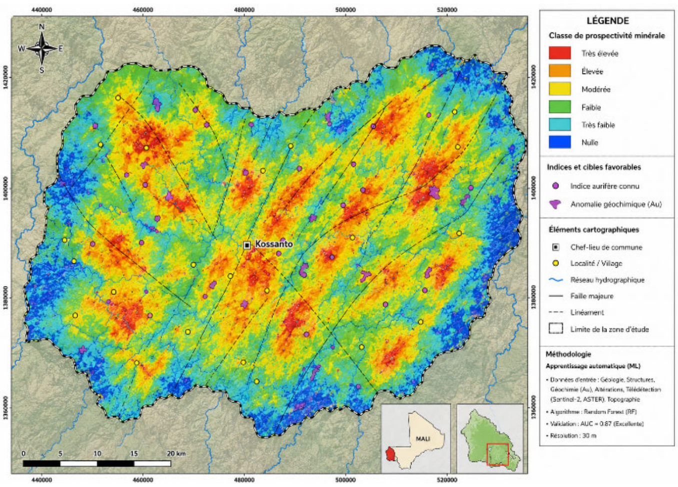


Figure 1. Machine Learning-based mineral prospectivity modeling map of the Kossanto area

Mineral Prospectivity Map and Identification of Prospective Areas

The combination of remote sensing and Machine Learning results enabled the generation of a mineral prospectivity map for the Kossanto region. This map differentiates several levels of mineral potential, including high, medium, and low favorability zones. The areas classified as having high prospectivity are mainly associated with sectors characterized by a favorable combination of geological factors, including the presence of favorable Birimian formations, major tectonic structures, hydrothermal alteration zones detected through remote sensing analysis, and significant spectral anomalies. These areas correspond to the most favorable geological environments for the concentration and deposition of gold-bearing hydrothermal fluids. The medium prospectivity zones represent areas where some favorable exploration criteria are present but where the influence of certain geological, structural, or spectral parameters remains limited. These zones may correspond to transitional environments requiring additional geological investigations and field validation before prioritizing exploration activities. The low prospectivity zones mainly include areas characterized by weak structural development, less favorable lithological units, limited hydrothermal alteration signatures, or the absence of significant spectral anomalies related to mineralization. These sectors are considered less favorable for immediate gold exploration compared with high and medium prospectivity zones. The resulting prospectivity map provides an effective decision-support tool for exploration planning by prioritizing target areas where multiple mineralization-controlling factors overlap. The spatial distribution of high-potential zones confirms the importance of integrating geological, structural, spectral, and topographic information within a Machine Learning framework for improving gold exploration strategies in the Kossanto region.

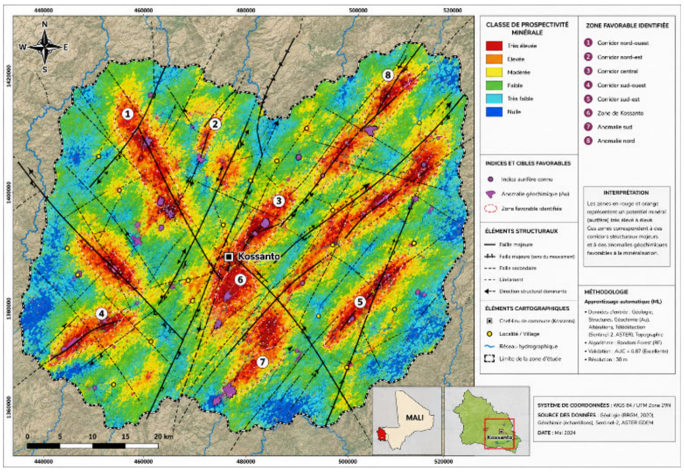


Figure 2. Mineral prospectivity map and identification of prospective zones in the Kossanto region, western

Validation of the Obtained Results

The comparison between the predictive maps generated by the models and geological field observations shows a good agreement between the areas identified as favorable by the algorithms and the sectors containing known gold occurrences. The anomalies detected by the models are mainly distributed around shear zones, lithological contacts, and areas affected by hydrothermal alteration. These results confirm the effectiveness of the integrated approach combining multispectral remote sensing, Geographic Information Systems (GIS), and artificial intelligence for mineral exploration. The developed methodology reduces uncertainties associated with conventional exploration approaches and improves the selection and prioritization of exploration targets within the Birimian terrains of Mali. The spatial consistency between predicted high-potential zones and geological indicators demonstrates the ability of Machine Learning models to capture the main geological controls responsible for gold mineralization. Overall scientific validation is based on the complementarity between the statistical performance of the models and their geological coherence. The combination of remote sensing data, field observations, geological information, and artificial intelligence techniques provides a robust framework for predictive gold prospectivity mapping. This integrated approach contributes to improving the accuracy of mineral exploration campaigns, optimizing field investigations, and reducing uncertainties related to traditional prospecting methods.

Table 1. Results of satellite data analysis and geological parameter assessment in the Kossanto area

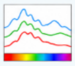
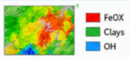
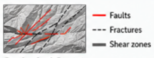
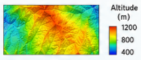
Analyzed Parameters	Methods Used	Results Obtained	Geological Interpretation
 Spectral Signatures	Sentinel-2 MSI and Landsat 8 OLI images, colored composites, band ratios	Identification of spectral variations between lithological units and altered zones	Evidence of contrasts between Birimian formations, granitoids and hydrothermalized zones
 Hydrothermal Alterations	Spectral indices (iron oxides, clays, hydroxyl minerals) and PCA	Detection of areas showing significant spectral anomalies	Identification of areas favorable to the circulation of mineralizing fluids
 Lithology	Integration of satellite data and geological information	Mapping of volcanic, volcano-sedimentary and granitoid units	Definition of lithological domains favorable to gold mineralization
 Geological Structures	Analysis of satellite images and field observations	Identification of faults, fractures and major shear zones	Evidence of the main structural controls on mineralization
 Topographic Data	Digital Terrain Model (DTM)	Extraction of morphological parameters (altitude, slope, relief)	Contribution to the characterization of geological settings favorable to mineral deposits

Table 2. Performance of Machine Learning Models Applied to Mineral Potential Prediction

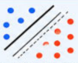
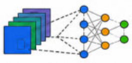
Models Used	Overall Accuracy (%)	Kappa Coefficient	AUC-ROC	RMSE	Interprétation
 Random Forest (RF)	89,6	0.86	0.92	0.21	Very good classification performance with strong robustness in handling complex data.
 Support Vector Machine (SVM)	86.9	0.82	0.89	0.25	Good class separation, but performance is more sensitive to model parameter settings.
 Convolutional Neural Network (CNN)	92.3	0.89	0.95	0.17	Best overall performance due to the automatic extraction of spatial and spectral features.

Table 3. Classification of Mineral Favorability Zones Obtained Using Machine Learning

Favorability Level	Main Identified Characteristics	Estimated Area (%)	Classification Criteria
High Favorability	Areas associated with major structures, lithological contacts, spectral anomalies and hydrothermal alterations	18.5	High probability of presence of gold mineralization
Medium Favorability	Sectors showing several favorable factors such as spectral signatures or moderately marked structures	34.2	Potential mineral intermediate requiring complementary investigations
Low Favorability	Domains with few structures, absence of significant alterations and low spectral anomalies	47.3	Low probability of economic mineralization

The mineral favorability map derived from the integration of satellite data and artificial intelligence models shows that 52.7% of the study area exhibits medium to high mineral potential, with the most promising targets concentrated around major tectonic structures and hydrothermal alteration zones. These results confirm the effectiveness of the approach combining multispectral remote sensing and Machine Learning for optimizing gold exploration in the Kossanto area.

DISCUSSION

The results obtained in this study demonstrate the relevance of integrating multispectral satellite imagery, geological data, and Machine Learning algorithms to improve predictive mapping of favorable zones for gold mineralization in the Kossanto area. This approach represents a significant advancement compared with conventional mineral exploration methods, which are often limited by the high costs of field surveys, the complexity of geological environments, and the difficulty of exploring large territories (Bonham-Carter, 1994; Carranza, 2008).

Contribution of Multispectral Remote Sensing and Machine Learning to Gold Exploration

The analysis of Sentinel-2 MSI and Landsat 8 OLI satellite data enabled the identification of spectral signatures associated with major lithological units and hydrothermal alteration zones. These results confirm the effectiveness of multispectral remote sensing for detecting indicator minerals such as iron oxides, clay minerals, and hydroxyl-bearing minerals, which represent important markers of hydrothermal gold systems (Sabins, 1999; Van der Meer *et al.,* 2012).Within the Birimian geological context of West Africa, these spectral signatures improve the discrimination between volcanic, volcano-sedimentary, and granitoid formations associated with metallogenic processes (Feybesse *et al.,* 2006). The observed relationship between spectral anomalies, tectonic structures, and favorable zones identified by the models confirms the major role of structural controls in the emplacement of gold mineralization in Kossanto. Shear zones, fractures, and lithological contacts constitute preferential pathways for the circulation of hydrothermal fluids responsible for gold concentration. This interpretation is consistent with the orogenic gold deposit model of the Birimian greenstone belts of the West African Craton (Groves *et al.,* 2003; Goldfarb *et al.,* 2005).The performances achieved by the Machine Learning models demonstrate the effectiveness of these techniques for modern mineral exploration. The Convolutional Neural Network (CNN) model achieved the highest performance due to its ability to automatically extract complex relationships between spectral, spatial, and geological variables. These results are consistent with the findings of Maxwell et al. (2018) and Dramsch (2020), who highlighted the importance of deep learning approaches for the analysis of multidimensional geoscientific datasets. The Random Forest (RF) model also showed excellent classification capability due to its robustness against noisy data and its ability to integrate multiple explanatory variables. These performances confirm its relevance for predictive mineral resource mapping applications (Breiman, 2001).Although slightly less efficient, the Support Vector Machine (SVM) model remains effective for class separation when datasets exhibit complex distributions and nonlinear relationships (Cortes & Vapnik, 1995).The integration of model outputs within a Geographic Information System (GIS) environment enabled the generation of a mineral favorability map capable of ranking priority areas for exploration activities. This approach reduces uncertainties associated with conventional exploration methods and allows more efficient allocation of human and financial resources during mineral exploration campaigns (Carranza, 2008).

Study Limitations and Perspectives for Improvement

Despite the satisfactory results obtained, this study presents several limitations that should be considered when interpreting the results. The first limitation concerns the spatial resolution of the satellite images used. Although Sentinel-2 and Landsat 8 data are suitable for regional-scale studies, their spatial resolution may limit the detection of small mineralized structures or geological bodies with limited spatial extent.

Future use of very high spatial resolution or hyperspectral data could improve the accuracy of mineralogical characterization and enhance the identification of mineral exploration targets. A second limitation relates to the availability and quality of training datasets used for Machine Learning models. The performance of algorithms strongly depends on the number, spatial distribution, and representativeness of reference points. An insufficiently diversified training database may introduce prediction biases and reduce the generalization capability of the models (Hastie *et al.,* 2009).Another constraint is associated with the limited availability of complementary geo scientific datasets, particularly detailed geochemical data, high-resolution geophysical information, and laboratory mineralogical analyses. The integration of these additional datasets would improve the understanding of metallogenic processes and increase the reliability of mineral favorability maps.

Furthermore, the artificial intelligence models used in this study may present limitations in terms of interpretability, particularly for Deep Learning approaches such as Convolutional Neural Networks (CNNs). Although these models generally provide higher predictive performance, understanding the internal relationships between input variables and model outputs remains challenging. The development of Explainable Artificial Intelligence methods could improve the geological interpretation of predictions and increase confidence in AI-based exploration approaches. Finally, the validation of the results remains mainly based on the available datasets and requires additional field investigations to confirm the new exploration targets identified by the models. Future studies should incorporate exploration drilling, detailed geochemical analyses, and high-resolution geophysical surveys to validate the economic potential of areas classified as having high mineral favorability.

CONCLUSION

This study demonstrated the effectiveness of an integrated approach based on multispectral satellite imagery, Geographic Information Systems (GIS), and Machine Learning algorithms for mineral exploration in the Kossanto area, western Mali. The main objective was to assess the contribution of artificial intelligence in identifying favorable zones for gold mineralization using geological, structural, and spectral datasets. The results show that Sentinel-2 MSI and Landsat 8 OLI satellite imagery provide valuable information for extracting lithological characteristics, tectonic structures, and hydrothermal alteration zones. The spectral indices derived from these datasets enabled the detection of anomalies associated with iron oxides, clay minerals, and hydroxyl-bearing minerals, which are important indicators of hydrothermal alteration processes. The integration of satellite, geological, and structural data into Machine Learning models significantly improved the prediction of favorable mineralization zones. The Random Forest, Support Vector Machine (SVM), and Convolutional Neural Network (CNN) models showed good predictive performance, with the CNN model achieving the highest efficiency due to its ability to analyze complex relationships among multiple input variables. The resulting mineral favorability map represents an effective decision-support tool for guiding future exploration campaigns toward priority areas. The identified favorable zones are mainly controlled by major tectonic structures, lithological contacts, and hydrothermal alteration zones, confirming the importance of geological controls in gold mineralization within the Birimian terranes of Mali. However, the results remain constrained by the spatial resolution of satellite datasets, the availability and representativeness of training data, and the limited integration of complementary datasets, particularly geochemical and geophysical information. In conclusion, the combination of multispectral remote sensing, GIS, and Machine Learning constitutes an innovative and efficient approach for gold exploration in the Birimian geological domains of Mali. This methodology contributes to reducing exploration uncertainties, optimizing exploration costs, and improving the selection and prioritization of mineral exploration.

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