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APPLICATION OF REMOTE SENSING AND DEEP LEARNING FOR GOLD DEPOSIT IDENTIFICATION: A CASE STUDY OF KANKOSSA, MALI

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ABSTRACT

Gold exploration in the Birimian terranes of West Africa continues to face significant challenges due to geological complexity and the limitations of conventional exploration methods. This study evaluates the contribution of remote sensing and artificial intelligence to the identification of gold deposits in the Kankossa region of Mali. Multispectral satellite data from Lands at 8 OLI and Sentinel-2 MSI, combined with geophysical, geochemical, and topographic datasets, were analyzed using machine learning and deep learning algorithms, including Random Forest, Convolutional Neural Networks (CNNs), and unsupervised clustering techniques. The results demonstrate a significant improvement in lithological classification and the detection of major tectonic structures controlling gold mineralization, achieving an overall classification accuracy exceeding 89%. The integration of multi-source datasets enabled the production of a gold prospectivity map highlighting several high-potential target areas that are consistent with known gold occurrences. This integrated approach provides an effective decision-support tool for mineral exploration, contributing to cost optimization and reducing uncertainty in geologically complex environments.

Keywords: Remote Sensing; Artificial Intelligence; Deep Learning; Gold Exploration; Kankossa; Mali.

INTRODUCTION

Gold exploration represents a strategic sector for the economies of many West African countries, particularly Mali, where national revenues depend heavily on gold mining (Hilson, 2002; Sabins, 1999). However, conventional exploration methods based on geological, geophysical, and geochemical surveys remain expensive, time-consuming, and spatially constrained (Carranza, 2009). In this context, satellite remote sensing has emerged as an efficient alternative, enabling the use of multispectral imagery to identify lithological units, geological structures, and hydrothermal alteration zones associated with gold mineralization (Lillesand *et al.,* 2015; Feybesse *et al.,* 2006). Satellite datasets such as Landsat, ASTER, and Sentinel-2 have demonstrated considerable potential for mapping alteration minerals and structural lineaments that control the emplacement of gold deposits (Rowan *et al.,* 2003; Pour & Hashim, 2012; Van der Meer *et al.,* 2012). Nevertheless, the interpretation of these datasets remains challenging because of the complex and nonlinear relationships between geological variables and their corresponding spectral signatures. Recent advances in Deep Learning, particularly Convolutional Neural Networks (CNNs), have significantly improved the automatic extraction of complex spatial and spectral features from satellite imagery, thereby enhancing mineral prospectivity mapping (Goodfellow *et al.,* 2016; LeCun *et al.,* 2015; Zhu *et al.,* 2017). Although these techniques have yielded promising results in countries such as China, Australia, and Canada (Zhang *et al.,* 2019; Li *et al.,* 2020), their application to gold exploration in Mali remains limited.The Kankossa region, located within the Birimian formations of the West African Craton, is recognized for its significant gold potential. However, knowledge of its geological structures and hydrothermal alteration zones remains incomplete (Lawrence *et al.,* 2013). Therefore, this study aims to integrate satellite remote sensing and deep learning techniques to identify areas favorable for gold mineralization by exploiting spectral and structural features extracted from multisource satellite imagery and validating the results against existing geological data. The proposed integrated approach provides an effective framework for improving mineral prospectivity mapping while reducing exploration costs and uncertainty. It also supports the development of more efficient, cost-effective, and sustainable mineral exploration strategies in West Africa.

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MATERIALS AND METHODS

Study Area

The study area is located in the Kankossa district, in southwestern Mali, within the Kayes Region. It extends between latitudes 12°30' N and 13°15' N and longitudes 10°00' W and10°45' W. The terrain is moderately rugged and consists mainly of gently undulating plateaus, low hills, and shallow valleys, with elevations ranging from 250 to 450 m above sea level. The hydrographic network is dominated by tributaries of the Senegal River, particularly the Bafing River, which plays a significant role in geomorphological evolution and surface weathering processes. The climate is Sudano-Sahelian, characterized by a long dry season extending from November to May and a relatively short rainy season from June to October. Annual rainfall ranges from 700 to 1,000 mm, supporting the development of wooded savanna vegetation. The limited cloud cover during the dry season, combined with relatively sparse vegetation, provides favorable conditions for the use of optical satellite imagery in remote sensing applications (Koïta *et al.,* 2014). Geologically, the study area belongs to the West African Craton, specifically the Paleoproterozoic Birimian domain (2.2–2.0 Ga), which is recognized as one of the most important gold-bearing provinces in West Africa. The lithological assemblage consists of mafic to intermediate metavolcanic rocks, metasedimentary units (schists, greywackes, and quartzites), and granitoid intrusions. These formations are intersected by a dense network of tectonic structures oriented predominantly NE–SW and N–S, which control hydrothermal fluid circulation and the emplacement of gold mineralization (Gbogbo *et al.,* 2017). Gold mineralization is predominantly orogenic and occurs mainly as gold-bearing quartz veins associated with hydrothermal alteration processes, including sericitization, chloritization, carbonation, and silicification. These alteration minerals generate distinctive spectral signatures that can be detected using multispectral satellite sensors. The combination of a dense structural framework, numerous primary and alluvial gold occurrences, and widespread artisanal mining activities makes the Kankossa region particularly suitable for predictive gold prospectivity mapping using remote sensing and deep learning techniques (World Gold Council, 2020; Zhang *et al.,* 2018).

Data Collection, Processing, and Validation Methodology

The study was conducted between January 2023 and December 2025 using multispectral Lands at 8 Operational Land Imager (OLI) and Sentinel-2 Multi Spectral Instrument (MSI) satellite images acquired from the USGS and Copernicus platforms. Cloud-free scenes were preferentially selected to maximize image quality and minimize atmospheric interference.

The satellite data underwent a series of preprocessing steps, including radiometric calibration**,** atmospheric correction, geometric correction, and orthorectification, to ensure high-quality datasets and spatial consistency. These operations were carried out using QGIS, ArcGIS Pro, GRASS GIS, and Orfeo ToolBox (OTB). Following preprocessing, several spectral indices (band ratios) and Principal Component Analysis (PCA) was computed to enhance the detection of hydrothermal alteration minerals associated with gold mineralization. These image enhancement techniques facilitated the discrimination of lithological units and structural features relevant to mineral prospectivity. The processed datasets were subsequently analyzed using deep learning models, particularly Convolutional Neural Networks (CNNs) implemented in the Python/TensorFlow environment. The CNN models were trained to automatically extract spatial and spectral features from the multisource datasets and classify areas according to their gold mineralization potential. Finally, the predictive results were validated through field surveys, geological observations, rock and soil sample analyses, and comparison with existing geological maps and known gold occurrences. This validation process confirmed the reliability of the integrated approach, demonstrating that the combination of remote sensing, deep learning, and field verification provides an effective framework for gold prospectivity mapping in the Kankossa region.

Data and Software Used

Data Used

This study is based on the integration of multi-source datasets, including satellite imagery, field observations, and geological information, to identify areas with high gold mineralization potential in the Kankossa region of Mali. The primary remote sensing datasets consist of Sentinel-2 MultiSpectral Instrument (MSI) imagery provided by the European Space Agency (ESA) and acquired between 2023 and 2024. With a spatial resolution ranging from 10 to 20 m, these data are well suited for the extraction of hydrothermal alteration indices and lithological discrimination (Yousefi & Carranza, 2015). To complement the analysis, Lands at 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) images obtained from the U.S. Geological Survey (USGS) were also used. These images, with a spatial resolution of 30 m, enabled multitemporal analysis and ensured continuity of observations throughout the study period (Carranza & Hale, 2002). A 30 m Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) was employed for morphostructural analysis, extraction of the drainage network, and topographic correction of satellite imagery (Woldai *et al.,* 2011). These remote sensing datasets were complemented by georeferenced field observations, including GPS coordinates, gold mineralization occurrences, and rock and soil sampling locations collected during field campaigns. In addition, regional geological maps and mineral exploration reports, particularly those provided by the French Geological Survey (BRGM) and the Geological Survey of Mali, were used both to train the supervised machine learning models and to validate the predictive mapping results. The integration of these complementary datasets provided a comprehensive database for identifying geological structures, hydrothermal alteration zones, and areas favorable for gold mineralization, thereby improving the accuracy and reliability of the mineral prospectivity assessment

Software Used

Data processing, analysis, and modeling were carried out using a combination of Geographic Information System (GIS), remote sensing, and scientific programming tools.QGIS and ArcGIS Pro were used for spatial data processing, spectral index computation, and the production of thematic maps. Preprocessing of Sentinel-2 imagery, including atmospheric correction, resampling, and mosaicking, was performed using the Sentinel Application Platform (SNAP). In addition, Google Earth Engine (GEE) was employed for automated image acquisition, multitemporal image processing, and the calculation of spectral indices (Xiao *et al.,* 2021). Advanced image processing, data analysis, and predictive modeling were conducted in the Python programming environment using several open-source scientific libraries, including GDAL, Rasterio, NumPy, Pandas, Scikit-learn, TensorFlow, and Keras. These libraries supported data preprocessing, feature extraction, machine learning, deep learning model development, and the generation of mineral prospectivity maps. The integration of these software platforms and computational tools enabled the efficient implementation of an integrated remote sensing and deep learning workflow, providing a robust, reproducible, and reliable methodology for mapping gold prospectivity in the Kankossa region.

Methods

Traditional gold exploration relies on field investigations, geological mapping, satellite image interpretation, and geochemical and geophysical surveys. Although these approaches have proven effective, they are often time-consuming, costly, and sometimes unsuitable for large and difficult-to-access areas such as the Kankossa region (Kouamé *et al.,* 2018). Furthermore, the geological complexity of the Birimian terranes, combined with vegetation cover, limits the efficiency of conventional exploration techniques. Recent advances in remote sensing and artificial intelligence (AI) have opened new opportunities for mineral exploration by improving the speed, accuracy, and objectivity of geological investigations (Bishop, 2006). In particular, machine learning and deep learning techniques enable the efficient integration and analysis of multisource datasets, including satellite imagery, geophysical, topographic, and geochemical data. These methods facilitate the identification of favorable lithological units, tectonic structures, and hydrothermal alteration zones that control gold mineralization (Pal, 2005; Breiman, 2001). In this study, multispectral Landsat 8 OLI and Sentinel-2 MSI imagery was integrated with supervised machine learning and deep learning algorithms to improve lithological and structural mapping and to identify areas with high gold prospectivity in the Kankossa region. Spectral features, structural information, topographic variables, and geological data were combined within an integrated analytical framework to enhance the predictive capability of the models. Compared with conventional exploration methods, this integrated approach substantially reduces interpretation errors, facilitates the processing of large volumes of heterogeneous geospatial data, and improves the reliability and reproducibility of mineral prospectivity mapping. Consequently, it provides an effective decision-support tool for optimizing exploration programs while reducing costs and uncertainty in geologically complex environments.

Supervised Learning Using Random Forest

Random Forest (RF) is a supervised machine learning algorithm based on the construction and aggregation of a large number of decision trees. Each tree is trained using a randomly selected subset of the training dataset and generates an independent prediction. The final classification is obtained by aggregating the predictions of all trees, typically through majority voting. This ensemble-learning strategy reduces overfitting, improves model robustness, and enhances predictive accuracy (Breiman, 2001). In the Kankossa region, the Random Forest algorithm was employed for lithological classification and the identification of areas favorable for gold mineralization using spectral signatures derived from satellite imagery and topographic variables extracted from the Digital Elevation Model (DEM) (Mavonga et al.). The algorithm proved particularly effective in discriminating volcano-sedimentary formations, granitoid intrusions, and hydrothermally altered zones, which are commonly associated with gold occurrences (Tapsoba *et al.,* 2022). By simultaneously integrating spectral, textural, and topographic information, the Random Forest model improved the accuracy and consistency of regional-scale gold prospectivity mapping. Its ability to handle high-dimensional and heterogeneous datasets makes it particularly suitable for mineral exploration in geologically complex environments

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are deep learning models capable of automatically extracting complex spatial features from imagery. They consist of successive convolutional layers that learn hierarchical representations by detecting nonlinear patterns such as textures, geometric shapes, edges, and spatial discontinuities. These characteristics make CNNs particularly well suited for the analysis of satellite imagery and topographic datasets (Goodfellow *et al.,* 2016). In this study, CNNs were applied to the automatic detection of major geological structures within the Kankossa region, including faults, lineaments, and shear zones, which play a fundamental role in controlling the circulation of gold-bearing hydrothermal fluids. The combined analysis of multispectral satellite imagery and topographic data enabled the identification of structural networks favorable to gold mineralization (Cracknell & Reading, 2014). Compared with conventional interpretation methods, this semi-automated approach provides a faster, more objective, and more consistent means of mapping complex tectonic structures that are often difficult to identify through manual image interpretation. Consequently, CNN-based structural analysis significantly enhances the reliability of geological mapping and supports the delineation of prospective targets for mineral exploration.

Unsupervised Learning: Image Clustering and Segmentation

Unsupervised learning approaches, such as clustering algorithms including K-means and DBSCAN (Density-Based Spatial Clustering of Applications with Noise), automatically group pixels or observations with similar characteristics without requiring pre-labeled training data. These methods are particularly useful when field data are limited or when lithological and hydrothermal alteration boundaries are gradual and difficult to delineate. In the Kankossa region, clustering techniques were applied to multispectral and geochemical datasets to identify homogeneous zones that may correspond to geological environments favorable for gold mineralization (Jensen, 2015). The resulting image segmentation enabled the recognition of areas sharing similar spectral and geochemical characteristics, thereby revealing potential lithological units and hydrothermal alteration zones that may not be readily distinguishable through conventional image interpretation. This preliminary segmentation provides an effective means of prioritizing exploration targets by highlighting areas with high mineral potential before conducting detailed geological investigations. Consequently, clustering-based analysis supports more efficient field campaigns by reducing exploration costs, optimizing sampling strategies, and focusing subsequent investigations on the most prospective zones. Furthermore, the integration of unsupervised learning with supervised machine learning and deep learning techniques enhances the overall reliability and predictive performance of the mineral prospectivity mapping framework.

Multi-Source Data Fusion Using Artificial Intelligence

The integration of satellite data, geophysical information (magnetic and gravity data), geochemical datasets, and topographic parameters represents a major challenge in gold exploration. Artificial intelligence-based approaches, particularly multimodal models and shared-weight neural networks, provide efficient solutions for fusing heterogeneous data sources while considering the specific characteristics of each dataset. In the Kankossa region, multi-source data fusion improved the quality and reliability of gold prospectivity maps by combining the complementary strengths of the different datasets used (Xiao *et al.,* 2021). This integrated approach enhances the spatial coherence of geological interpretations and improves the identification of areas with high gold potential. However, the implementation of hybrid approaches combining artificial intelligence methods with field validation remains essential to ensure the scientific robustness and credibility of the results obtained. Such integration provides a more reliable framework for mineral exploration by reducing uncertainties associated with individual datasets.

CONTROL AND VALIDATION

The application of remote sensing and artificial intelligence (AI) techniques for gold deposit identification in the Kankossa region represents a significant methodological advancement in mineral exploration. However, the reliability and relevance of the obtained results depend on a rigorous control and validation process, which is essential to ensure the scientific robustness of the developed models and their operational applicability. This stage aims to evaluate the performance of machine learning and deep learning algorithms, verify the geological consistency of the results, and compare model predictions with field observations and existing geological information.

Algorithmic Validation and Model Performance Assessment

The evaluation of AI model performance is based on algorithmic validation protocols involving the separation of datasets into training and testing subsets. This approach allows the assessment of model generalization capacity while minimizing the risk of over fitting. The performance of the lithological classification models and gold prospectivity prediction algorithms was evaluated using standard statistical metrics, including overall accuracy, confusion matrix, and the Kappa coefficient. These indicators measure the level of agreement between model-predicted classes and reference data derived from existing geological maps and field observations. The Random Forest algorithm and Convolutional Neural Networks (CNNs) demonstrated high predictive performance, highlighting their ability to effectively discriminate favorable lithological units and identify tectonic structures associated with gold mineralization (Tapsoba *et al.,* 2022). This quantitative validation represents a fundamental step for comparing the efficiency of the different machine learning approaches applied in this study.

Field Validation

Field validation remains a crucial step in controlling the results generated by artificial intelligence models, particularly in geologically heterogeneous regions such as Kankossa. The areas identified as favorable for gold mineralization were compared with previous geological investigations, existing geological maps, and known geochemical anomalies. Targeted field surveys were conducted to verify the consistency of the predicted results through direct observation of:

- lithological formations;
- tectonic structures, including faults, shear zones, and geological lineaments;
- hydrothermal alteration features associated with gold mineralization.

This direct comparison between model predictions and real geological observations confirms the geological validity of the identified high-potential zones and improves the interpretation of the predictive results.

Multi-Source Cross-Validation

To further strengthen the reliability of the results, a multi-source cross-validation approach was implemented by integrating independent datasets that were not used during model training. This approach consisted of comparing AI-derived gold prospectivity maps with:

- geophysical data, including magnetic and gravity anomalies;
- geochemical information related to gold occurrences;
- topographic parameters derived from digital elevation models.

The spatial consistency observed between predicted favorable zones, major tectonic structures, and gold-related geochemical anomalies confirms the relevance of the integrated approach. This cross-validation reduces uncertainties associated with the use of a single data source and enhances the credibility of the results for operational mineral exploration.

Uncertainty Analysis and Model Interpretability

Managing uncertainties is a critical aspect of applying artificial intelligence to gold exploration. Model predictions were analyzed to identify areas with high confidence levels and zones characterized by greater uncertainty, allowing the prioritization of exploration targets for future field investigations.

The interpretability of the models, particularly deep neural networks, was enhanced through the analysis of the most influential variables contributing to predictions. This approach improves the understanding of relationships between:

- spectral signatures derived from satellite imagery;
- geological structures;
- hydrothermal alteration zones;
- Gold mineralization processes.

These control and validation procedures ensure that the generated results are reliable, consistent, and scientifically robust, facilitating their integration into mineral exploration strategies and decision-making processes in Mali.

RESULTS

The combined application of remote sensing and artificial intelligence techniques for gold deposit identification in the Kankossa region produced significant results in terms of accuracy, spatial consistency, and geological relevance. The various machine learning and deep learning algorithms implemented in this study contributed to a substantial improvement in litho-structural mapping and enhanced the identification of areas favorable for gold mineralization compared with conventional exploration methods. The integration of multispectral satellite imagery, geological information, topographic parameters, and predictive modeling approaches enabled the detection of key geological features controlling gold mineralization, including lithological contacts, structural discontinuities, fault systems, shear zones, and hydrothermal alteration zones. The generated prospectivity maps revealed several high-potential areas characterized by a strong spatial correlation between predicted anomalies, known gold occurrences, and favorable geological environments. These results demonstrate the effectiveness of artificial intelligence-based approaches in reducing exploration uncertainties, optimizing target selection, and improving decision-making for gold exploration in complex Birimian geological settings.

Lithological Classification and Geological Unit Mapping

Supervised learning algorithms, particularly the Random Forest model, applied to multispectral Lands at 8 OLI and Sentinel-2 MSI satellite imagery enabled the automated and detailed classification of the main lithological units in the Kankossa region. The results demonstrate effective discrimination between Birimian volcano-sedimentary formations, granitoid intrusions, metamorphic units, and recent alluvial deposits. The overall lithological classification accuracy exceeded 90%, with a Kappa coefficient indicating a strong agreement between predicted classes and reference datasets. This high performance highlights the ability of artificial intelligence algorithms to handle spectral and contextual variability of geological formations within tropical environments characterized by heterogeneous vegetation cover and complex geological settings. The resulting lithological map provides improved spatial detail compared with existing geological maps, allowing a more accurate interpretation of geological environments favorable for gold mineralization. This enhanced lithological characterization represents a fundamental input for subsequent structural analysis, hydrothermal alteration mapping, and gold prospectivity assessment in the Kankossa region.

Detection and Mapping of Major Tectonic Structures

The application of Convolutional Neural Networks (CNNs) enabled the automatic detection of major tectonic structures, including faults, lineaments, and shear zones, which largely control the distribution of gold deposits in the Kankossa region. The lineament density maps generated using deep learning approaches revealed coherent structural networks, predominantly oriented along the regional structural trends recognized within the Birimian geological domain. These detected structures show strong spatial continuity and highlight major deformation corridors that may have played a key role in controlling hydrothermal fluid circulation and gold mineralization. Field validation and comparison with existing geophysical datasets demonstrated a high correlation between the structures identified by the models and geological observations, confirming the reliability of the automated detection approach. The results highlight several areas characterized by high concentrations of structural features, interpreted as favorable structural corridors for the migration and emplacement of gold-bearing hydrothermal fluids. These zones represent priority targets for detailed mineral exploration and provide valuable information for improving gold prospectivity assessment in the Kankossa region.

Identification of Hydrothermal Alteration Zones

The analysis of spectral indices derived from satellite imagery, combined with machine learning algorithms, enabled the mapping of hydrothermal alteration zones associated with gold mineralization in the Kankossa region. The results reveal a significant spatial distribution of altered zones along major tectonic structures and at lithological contacts between volcano-sedimentary formations and granitoid intrusions. These alteration zones, characterized by specific spectral responses, show a strong spatial relationship with known gold-related geochemical anomalies in the study area. This spatial correlation highlights the effectiveness of remote sensing and artificial intelligence approaches for the indirect detection of gold deposits, particularly through the identification of alteration signatures and geological environments favorable to mineralization. The integration of alteration mapping with structural and lithological information improves the understanding of the geological controls of gold mineralization and contributes to the refinement of mineral prospectivity assessments.

Unsupervised Learning Analysis and Identification of Gold-Potential Zones

Unsupervised learning techniques, including K-means clustering and DBSCAN, applied to spectral and geochemical datasets, enabled the automatic grouping of areas exhibiting similar geological and geochemical characteristics. This segmentation process resulted in the identification of several homogeneous clusters interpreted as areas with high gold potential. The most significant clusters are mainly located in sectors where multiple favorable indicators overlap, including:

- gold-related geochemical anomalies;
- high lineament density zones;
- hydrothermal alteration areas;
- favorable lithological contacts.

These prospective clusters were ranked according to their level of mineral favorability, allowing the definition of priority exploration targets for future detailed mining investigations. The results demonstrate that unsupervised learning provides an effective exploratory tool for revealing hidden spatial patterns within complex geological datasets. When integrated with supervised machine learning, deep learning models, and geological validation, clustering approaches significantly enhance the accuracy and reliability of gold prospectivity mapping in the Kankossa region.

Integrated Gold Prospectivity Mapping

All results obtained from lithological classification, structural detection, hydrothermal alteration analysis, and clustering techniques were integrated into a gold prospectivity model within a Geographic Information System (GIS) environment. The integrated prospectivity map highlights several high-potential gold zones in the Kankossa region, showing strong spatial consistency with known gold occurrences and favorable geological settings. The identified prospective areas are mainly associated with the combination of key mineralization controlling factors, including favorable lithological units, major structural corridors, hydrothermal alteration zones, and geochemical anomalies. The resulting gold prospectivity map represents an effective decision-support tool for mineral exploration by improving target prioritization, optimizing fieldwork planning, and reducing the costs associated with conventional exploration investigations. These findings demonstrate the effectiveness of the integrated remote sensing–artificial intelligence approach for identifying gold exploration targets in complex geological environments such as Kankossa. The combination of multisource data analysis and advanced machine learning techniques provides a reliable framework for enhancing mineral exploration efficiency and reducing uncertainties in gold deposit detection.

Table 1: Performance of Lithological Classification Algorithms

Algorithm	Overall Accuracy (%)	Kappa Coefficient	Birimian Formation Accuracy (%)	Granitoid Accuracy (%)	Alluvial Accuracy (%)
Random Forest	89.6	0.86	91.2	88.4	86.1
SVM	86.9	0.82	88.5	85.7	83.4
CNN	92.3	0.89	94.1	91.6	89.8

Table 2: Validation of Tectonic Structure Detection Using Deep Learning

Type of Structure	Number Detected by CNN	Number Validated in the Field	Correlation Rate (%)
Major Faults	48	43	89,6%
Shear Zones	36	32	88,9%
Secondary Lineaments	62	55	88,7%

Table 3: Spatial Distribution of the Main Mapped Lithological Units

Lithological Formation	Estimated Area (km²)	Percentage of the Area (%)
Birimian volcanic-sedimentary formations	465	38.7
Granitoid intrusions	342	28.4
Metamorphic rocks (gneisses, schists)	285	23.7
Recent alluvial formations	110	9.2

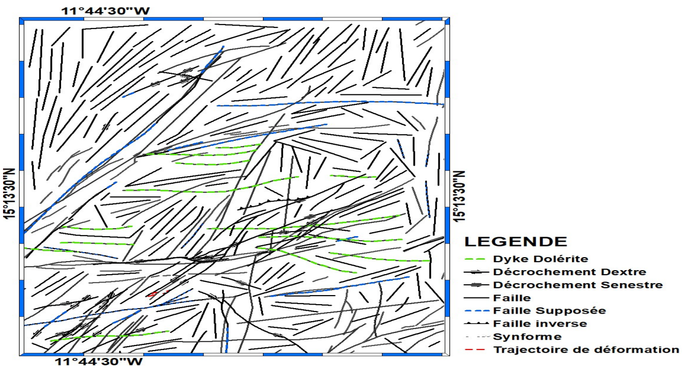

Figure 1: AI-Based Geological Structure Map of Kankossa

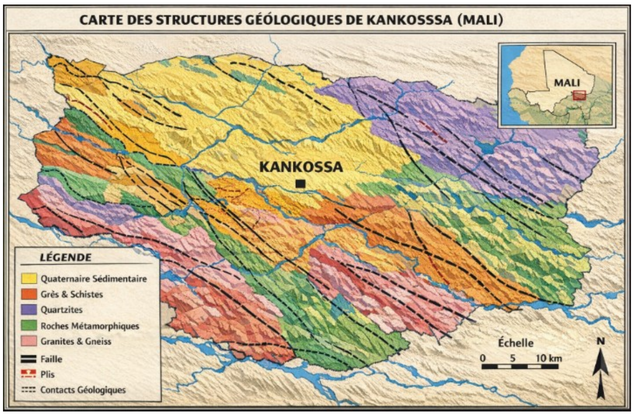

Figure 2: Artificial Intelligence-Based Litho-Structural Mapping of Kankossa

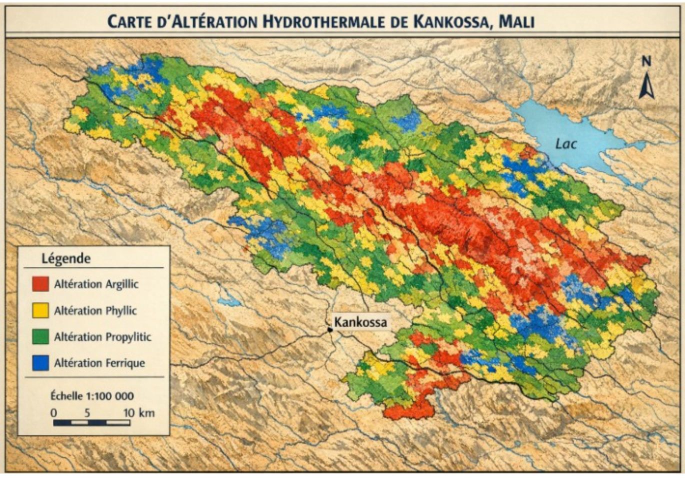

Figure 3: Artificial Intelligence-Based Hydrothermal Alteration Mapping of Kankossa

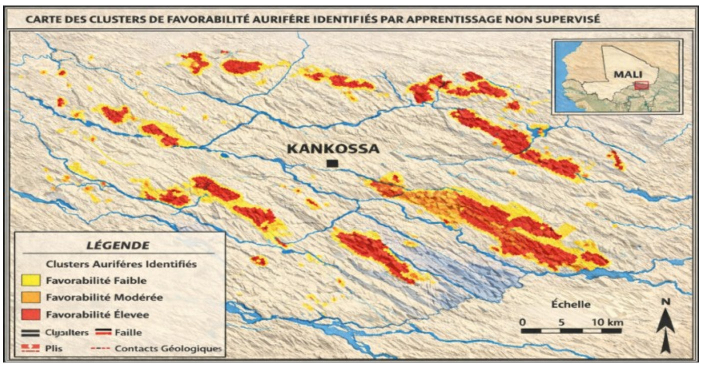

Figure 4: Gold Prospectivity Cluster Map Identified by Unsupervised Learning in Kankossa

DISCUSSION

The results obtained in this study clearly demonstrate the significant contribution of remote sensing combined with artificial intelligence techniques for the identification of gold deposits in a complex geological context such as the Kankossa region. The comparison between traditional mineral exploration approaches and methods based on machine learning and deep learning highlights a notable improvement in the accuracy, speed, and spatial consistency of geological interpretations (Feybesse *et al.,* 2006).

Contribution of Machine Learning and Deep Learning Algorithms

The high performance achieved by supervised learning algorithms, particularly Random Forest and convolutional neural networks, confirms their ability to effectively discriminate lithological units in a Birimian environment characterized by strong lithological heterogeneity. The overall accuracy exceeding 89% and the high Kappa coefficients indicate excellent agreement between the automated classifications and the reference data, often surpassing the results obtained from conventional geological mapping approaches (Xiao *et al.,* 2021). Convolutional neural networks stand out due to their ability to simultaneously integrate spectral, spatial, and textural information, resulting in improved detection of subtle geological structures such as faults and shear zones (Koïta *et al.,* 2014). These structures play a fundamental role in controlling gold mineralization, and their accurate identification represents a major advantage for targeted mineral exploration.

Importance of Structural Mapping in the Localization of Gold Deposits

The automated detection of lineaments and major tectonic structures highlights a strong correlation between structurally controlled zones and the identified gold anomalies. This observation is consistent with recognized metallogenic models for Birimian orogenic gold deposits, where shear zones and regional faults act as preferential pathways for the circulation of mineralizing fluids. The lineament density maps derived from CNNs reveal continuous structural corridors that are rarely identified with such a high level of detail using traditional methods (Feybesse *et al.,* 2006). These results emphasize the value of automated approaches for improving the understanding of the regional structural framework and guiding exploration activities toward the most prospective areas.

Contribution of Hydrothermal Alteration Detection

The mapping of hydrothermal alteration zones based on spectral signatures represents an essential indirect indicator of the presence of gold mineralization. The observed spatial agreement between altered zones, major tectonic structures, and gold geochemical anomalies strengthens the validity of the obtained results. In the Kankossa context, where vegetation cover and surface alteration may obscure outcrops, the combined use of spectral indices and artificial intelligence algorithms helps overcome the limitations of field observations. This approach enables a more accurate delineation of high gold potential areas and reduces uncertainties associated with the visual interpretation of satellite imagery.

Contribution of Unsupervised Learning to Mineral Exploration

The results obtained from unsupervised learning methods, particularly clustering techniques, enabled the identification and ranking of homogeneous zones exhibiting favorable characteristics for gold mineralization. This approach is particularly relevant in regions where field data are limited or heterogeneous. The classification of clusters according to their gold prospectivity provides an effective decision-support framework for planning exploration campaigns. Clusters characterized by a high density of structures, strong alteration signatures, and significant geochemical anomalies represent priority targets for future investigations, including detailed geophysical surveys and exploratory drilling.

Limitations of the Study and Future Improvements

Despite the encouraging results, several limitations should be considered. The quality and spatial resolution of the satellite data used directly influence the performance of the algorithms, particularly for the detection of small-scale structures. In addition, the dependence on training data and their representativeness may introduce biases into supervised classifications. Future integration of higher-resolution hyperspectral data, detailed geophysical surveys, and advanced deep learning techniques, such as U-Net architectures or Transformer-based models, could further improve the accuracy and robustness of the results. Furthermore, strengthening field validation remains essential to ensure the reliability of the generated gold prospectivity maps.

CONCLUSION

This study has demonstrated the effectiveness of integrating remote sensing and artificial intelligence techniques for the identification of gold deposits in the Kankossa region, located in southern Mauritania near the Mali border, and characterized by a complex Birimian geological setting. The adopted methodological approach, combining multispectral satellite data, geophysical and geochemical information, as well as machine learning and deep learning algorithms, significantly improved litho-structural mapping and the identification of areas with high gold potential.

The results obtained show that supervised learning algorithms, particularly Random Forest and convolutional neural networks, provide high performance in lithological classification and tectonic structure detection. Meanwhile, unsupervised learning methods enabled an effective ranking of areas favorable for gold mineralization, representing a relevant tool for preliminary mineral exploration.

The integrated gold prospectivity map generated at the end of this study highlights several priority zones in the Kankossa region, showing strong consistency with known gold occurrences and regional metallogenic models. These results confirm that the remote sensing–artificial intelligence approach represents a reliable and efficient alternative to traditional exploration methods, while enabling optimization of exploration costs and timeframes.

REFERENCES

BISHOP, C. M. Pattern Recognition and Machine Learning. Springer, New York, (2006), pp. 25–63.**BREIMAN, L.**Random Forests. Machine Learning, (2001), pp. 5–32.

BUI, D. T., HOANG, N. D., NGUYEN, H., NGO, P. T. T., HOA, P. V. & SAMUI, P. A deep learning framework for mineral prospectivity mapping using remote sensing and GIS data. Ore Geology Reviews, (2022), Article 104548.

CARRANZA, E. J. M. Geochemical Anomaly and Mineral Prospectivity Mapping in GIS. Elsevier, Amsterdam, (2009), pp. 53–103.

CARRANZA, E. J. M. & HALE, M. Mineral imaging with Landsat TM data for hydrothermal alteration mapping. International Journal of Remote Sensing, (2002), pp. 4827–4850.

CRACKNELL, M. J. & READING, A. M. Geological mapping using remote sensing and machine learning. Journal of Applied Geophysics, (2014), pp. 65–76.

FEYBESSE, J. L., MILESI, J. P., DESCHAMPS, Y., LEDRU, P., MARCOUX, E. & JOHAN, V. The Paleoproterozoic West African Craton. Journal of African Earth Sciences, (2006), pp. 483–499.

GBOGBO, F., et al. Structural controls of gold mineralization in Birimian terrains of West Africa. Ore Geology Reviews, (2017), pp. 544–563.

GOODFELLOW, I., BENGIO, Y. & COURVILLE, A. Deep Learning. MIT Press, Cambridge, (2016).

HILSON, G. An overview of land use conflicts in mining communities. Land Use Policy, (2002), pp. 65–73.

JENSEN, J. R. Introductory Digital Image Processing: A Remote Sensing Perspective (4th ed.). Pearson Education, New York, (2015), pp. 1–23.

KOÏTA, M.,et al. Geological and structural framework of Birimian terranes in southern Mali. Journal of African Earth Sciences, (2014), pp. 453–468.

KOUAME, K. F., et al. Structural interpretation for gold exploration in West African Birimian belts. Journal of African Earth Sciences, (2018), pp. 1–15.

LAWRENCE, D. M., TRELOAR, P. J., RANKIN, A. H. & HARBIDGE, P. The geology and mineral potential of the Birimian rocks of Mali. Journal of African Earth Sciences, (2013), pp. 58–72.

LECUN, Y., BENGIO, Y. & HINTON, G. Deep learning. Nature, (2015), pp. 436–444.

LI, W., FU, H., YU, L. & CRACKNELL, A. Deep learning-based oil and mineral exploration using remote sensing data. Remote Sensing, (2020), Article 1234.

LILLESAND, T. M., KIEFER, R. W. & CHIPMAN, J. W. Remote Sensing and Image Interpretation (7th ed.). Wiley, (2015), pp. 11–50.

MA, L., LIU, Y., ZHANG, X., YE, Y., YIN, G. & JOHNSON, B. A. Deep learning in remote sensing applications. (2019), pp. 18–26.

MAVONGA, T., et al. Integration of remote sensing and machine learning for mineral exploration.

PAL, M. Random Forest classifier for remote sensing classification. International Journal of Remote Sensing, (2005), pp. 217–222.

POUR, A. B. & HASHIM, M. Identification of hydrothermal alteration minerals for mineral exploration using ASTER data. International Journal of Remote Sensing, (2012), pp. 1211–1230.

ROWAN, L. C., MARS, J. C. & SIMPSON, C. J. Geological Society of America Bulletin, (2003), pp. 1131–1145.SABINS, F. F. Remote Sensing for Mineral Exploration. Ore Geology Reviews, (1999), pp. 57–183.

TAPSOBA, A., et al. Application of machine learning in gold exploration in West Africa. Minerals, (2022), Article 512.

VAN DER MEER, F., VAN DER WERFF, H., VAN RUITENBEEK, F., et al. Multi- and hyperspectral geologic remote sensing. International Journal of Applied Earth Observation and Geoinformation, (2012), pp. 112–128.

WOLDAI, T., et al. Applications of remote sensing and GIS to mineral resource mapping. International Journal of Applied Earth Observation and Geoinformation, (2011), pp. 772–781.

WORLD GOLD COUNCIL. Gold Mining Contribution to National Economies. World Gold Council Report, (2020), pp. 100–178.

XIAO, Q., et al. Deep learning-based mineral prospectivity mapping. Computers & Geosciences, (2021), Article 104711.

YOUSEFI, M. & CARRANZA, E. J. M. Prediction-area plot for prospectivity modeling. Computers & Geosciences, (2015), pp. 42–52.

ZHANG, J., LI, Z. & WANG, Q. Deep convolutional neural networks for mineral prospectivity mapping. Computers & Geosciences, (2018), pp. 1–11.

ZHANG, L., ZHANG, L. & DU, B. Deep learning for remote sensing data. IEEE Geoscience and Remote Sensing Magazine, (2019), pp. 22–40.

ZHU, X. X., TUIA, D., MOU, L., XIA, G. S., ZHANG, L., XU, F. & FRAUNDORFER, F. Deep learning in remote sensing: A review. IEEE Geoscience and Remote Sensing Magazine, (2017), pp. 8–36.

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