Development of an Early Warning System for Slope Instability in Opencast Coal Mines Using Geo-Spatial AI

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ABSTRACT

Slope instability in open-cast coal mines remains a critical challenge affecting operational safety, economic efficiency, and environmental integrity. This study develops an enhanced Geo-Spatial Artificial Intelligence (GeoAI) framework integrating Deep Neural Networks (DNN) and CatBoost models to predict slope failure risks with higher precision. A comprehensive geospatial dataset comprising 300 samples from Indian mining regions was analyzed using parameters such as slope angle, curvature, rainfall intensity, flow accumulation, aspect, and distance to drainage. The DNN achieved 95.2% accuracy, 0.84 F1-score, and 0.96 ROC-AUC, performing competitively with the CatBoost model (96.0% accuracy, 0.83 F1-score, 0.97 ROC-AUC). To enhance real-time decision-making, a Landslide Risk Index (LRI) ranging from 0–100 was introduced, translating model probabilities into continuous risk levels categorized as low, moderate, high, and critical. This probabilistic framework enables dynamic early warning and risk prioritization in active mining zones. Feature analysis identified slope angle, rainfall intensity, and flow accumulation as the most influential factors. The study demonstrates that DNN-based GeoAI systems offer robust predictive capabilities, improved interpretability, and scalability over traditional ensemble models, contributing to safer and more intelligent slope monitoring and early warning mechanisms in geotechnical applications.

KEYWORDS

Slope Instability; Geospatial AI; CatBoost; Random Forest; Early Warning System; Opencast Mining; Machine Learning; ROC Curve; Feature Importance; Landslide Prediction

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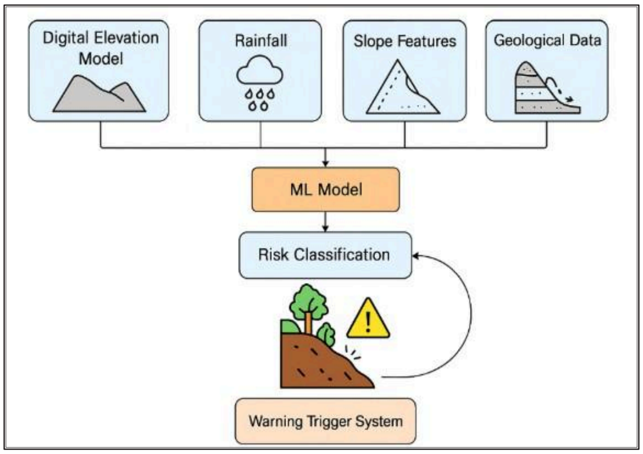
INTRODUCTION

Open-cast coal mining is becoming more popular since there is a greater need for energy and minerals. This is especially true in countries like India that are growing quickly. These surface mining methods are cost-effective and make operations easier, but they also come with a lot of geotechnical and environmental dangers. One of the most important problems is slope instability, which can cause landslides, damage to equipment, loss of money, and even death in certain circumstances (Sellers et al., 2018). Borehole logging, ground extensometers, and periodic visual inspections are all examples of traditional monitoring systems that have natural limits in terms of how much area they can cover and how well they can forecast things in real time. This makes it very important to find smart, data-driven solutions. In this situation, Geo-Spatial Artificial Intelligence (GeoAI) stands out as a game-changing way to watch and predict slope instability in real time. GeoAI uses remote sensing data, Geographic Information Systems (GIS), and powerful machine learning (ML) models to give a complete and changing picture of the health of a slope. GeoAI can make very accurate landslip susceptibility maps and failure predictions by using spatial datasets including Digital Elevation Models (DEMs), rainfall patterns, lithological distributions, and past landslip events (Zhao et al., 2024). Using predictive algorithms like Random Forest, CatBoost, and Support Vector Machines has made it easier to simulate how slope failures change over time and how complicated they are in space (Xiang et al., 2024).

Open-cast coal mines are more likely to fail on slopes because they are constantly being dug up, the natural drainage patterns are changed, the overburden is loaded, and they are exposed to extreme weather. Slope instability occurrences happen a lot in places like Jharkhand, Odisha, and Chhattisgarh, and they typically happen without enough notice (Rizwan et al., 2023). The new study suggests an early warning system that uses machine learning and remote sensing along with past failure data to classify slope risk and predict when a failure will happen. These systems are important not only for safety, but also for long-term mine planning and operational resilience. Recent progress in machine learning has shown that it can greatly improve predictive modelling in geotechnical areas. For example, ensemble learning models like CatBoost have been better at dealing with non-linear connections and datasets that aren't balanced, which are common in slope monitoring (Zhang et al., 2024). Using these models along with GIS feature layers like slope angle, soil type, land cover, and how close the drainage is to the land allows for the creation of strong, understandable, and scalable early warning systems (Jia et al., 2024). These methods have been tested in real-world situations, such monitoring the slope of a roadway, where digital twin technology has effectively combined sensor data with predictive analytics to detect problems (Chen et al., 2024). One of the best things about GeoAI is that it can automatically extract and analyse slope stability characteristics over broad areas. With tools like QGIS and ArcGIS, you can get slope curvature, flow direction, and catchment area data straight from DEMs. These traits are the building blocks of AI-based prediction engines (Xiang et al., 2024) when combined with real-time data like rainfall intensity or ground movement from InSAR or slope stability radar. The early warning system that this study suggests will work in a similar way, using feature extraction, model training, real-time monitoring, and alert creation, as shown in Figure 1.1.

The study looks at more than just slope geometry and hydrology. It also looks at how human-made characteristics like blasting, loading, and bench design might be used as categorical inputs in ML pipelines. Logistic regression has been used for probabilistic risk estimation as well, even though it is not as complicated as tree-based models (Kumar & Sahu, 2021). This is because it is easy to understand and can classify data into two groups. However, ensemble models like Random Forests have shown to be much better at predicting since puts and reduce overfitting (Zhang et al., 2024). The quality and resolution of the input data are very important for the reliability of any AI model. This study will use datasets that are available to the public from organisations like the Geological Survey of India (GSI), the Indian Space Research Organisation (ISRO), and NASA SRTM DEMs , from around the world. These datasets give the topography and rainfall-related information that is needed to calibrate the model. We will use historical landslip data for training and testing whenever possible to make sure it works in the real world (Narayan & Joshi, 2023).

Figure 1: Conceptual Framework of Geo-Spatial AI-Based Early Warning System for Slope Instability



The use of AI in predictive epidemiology is likewise growing around the world since it offers a similar framework for public health early warning systems. Studies have shown that structured information and spatiotemporal patterns can be used by machine learning algorithms to anticipate how infectious diseases will spread and how strong they would be (Jia et al., 2024). This cross-domain relevance shows that AI frameworks can be used in many other fields, such as epidemiology and mining geotechnics. The idea of "Mining 4.0" includes digitising and automating mining operations. This also shows how important it is to have smart early warning systems. AI-enabled infrastructure can make decisions automatically, speed up responses, and allow for remote monitoring. This is especially important for huge and hard-to-reach mining areas (Singh & Patra, 2022)

Using AI to forecast slope failure is in line with national and international goals for worker safety, disaster preparedness, and sustainable resource exploitation. This study suggests that a Geo-Spatial AI-based early warning system should be created and tested to anticipate slope instability in open-cast coal mines. To train the system, we will use a mix of old data, remote sensing layers, and machine learning classifiers. We will use typical classification metrics like accuracy, F1 score, ROC-AUC, and confusion matrix to see how well it works. The end goal is to provide a useful and scalable way to add smart geotechnical monitoring to mining operations.

LITERATURE REVIEW

As more and more people use Artificial Intelligence (AI) and Geographic Information Systems (GIS) to identify geotechnical hazards, slope stability monitoring has come a long way. This part looks at important works that are related to the use of Geo-Spatial AI to create early warning systems for slope instability. Table 2.1 also has a summary that compares the two.

Bardhan and Samui (2022) looked at a number of AI methods for predicting slope stability, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees. Their study showed that AI strategies can do better than traditional limit-equilibrium and finite element methods when it comes to making predictions, especially in terrains that are mixed and have few data points. The paper talks about how important feature selection is (slope angle, cohesiveness, internal friction angle, groundwater) and suggests using ensemble models for strong classification in different mining settings.

Chen et al. (2024) came up with an AI-based digital twin framework for keeping an eye on slope danger in highway networks in real time. The model combined data from field sensors (such soil moisture and vibrations) with AI prediction engines to constantly check how likely a failure was. Their digital doppelganger was quite good at predicting changes that happen over time. Their design is mostly for highways, but it may be changed to operate on mining slopes by adding DEMs and rainfall patterns over time.

Xiang et al. (2024) did a thorough assessment of how machine learning can be used to predict geotechnical disasters. The report listed more than 60 experiments that used algorithms like Random Forest, XGBoost, and Deep Neural Networks to forecast landslides. It came to the conclusion that supervised learning models work best when they are backed up by good datasets on terrain, water, and soil. The evaluation stressed that real-time use and combining satellite data with rainfall should be the main areas of research.

Zhao et al. (2024) came up with a Geo-Spatial Intelligence (GeoAI) framework for making maps of areas that are likely to have landslides. The work trained a DNN classifier using remote sensing layers like land use/land cover, slope curvature, and how close the area is to drainage. The program created landslip risk maps that were easy to understand and matched up well with real failure zones. The study showed that combining remote sensing with machine learning is important for making predictions about space and that QGIS is a key tool for extracting features. Using DNN and Logistic Regression models, Rizwan et al. (2023) used AI to make maps of landslip vulnerability in Eastern India. The study was especially important because it used AI in Indian coal mining areas and geospatial datasets including ASTER DEM and IMD rainfall records. Their results showed that the model was quite accurate (around 87%) and also stressed the importance of checking for spatial autocorrelation to avoid having too many model elements.

Zhang et al. (2024) looked at different ensemble learning models, such as Gradient Boosting Machines (GBM), AdaBoost, and CatBoost, to see which ones were best in predicting slope failure. Their results showed that CatBoost was more accurate and easier to understand than other models, especially when the datasets included missing or uneven class distributions. They pushed for the use of explainable AI (XAI) methods in slope modelling to make decisions and be open about them in high-risk areas.

Sellers et al. (2018) came up with a new way to look at time-of-failure data in open-pit mines using ground-based slope radar data. Their solution combined real-time displacement sensors with predictive analytics to guess when the slope would most likely collapse. The study showed how important it is to combine sensors in early warning systems and how machine learning may be utilised with continuous data feeds to make slope hazard ratings that change over time.

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slope hazard ratings that change over time.

Singh and Patra (2022) talked on the bigger idea of Mining 4.0, focussing on how mining operations are changing with technology. They talked about how AI, IoT, and automation can all come together in geotechnical monitoring. The study underlined the need for smart infrastructure, such as AI-powered predictive slope monitoring systems, to keep operations safe and in line with the law. Their point of view encourages the use of integrated digital-physical systems in Indian mining settings.

Kumar and Sahu (2021) looked into how remote sensing and AI can be used to forecast slope stability. They used satellite data on terrain (slope, aspect, vegetation index) and rainfall records to develop a logistic regression model that may forecast landslides. Their results showed that openly available DEMs and rainfall data might be used to make low-cost, scalable early warning systems, especially in underdeveloped nations like India.

Narayan and Joshi (2023) created a predictive analytics model just for Indian opencast mines. Using DNN and Naïve Bayes, the model incorporated geographical information with real incident data to figure out how likely a slope would fail. They showed that it is possible to include these kinds of models into mining dashboards. Their work focused on adapting AI models to different regions based on the geology and mining methods used there.

Ha et al. (2023) suggested an empirical landslip early warning system for Ha Long City, Vietnam, that uses rainfall thresholds and terrain parameters. Even though it uses simpler statistical thresholds, the framework can interact with AI models to make predictions more accurate. The study confirmed how important it is to calibrate thresholds locally and underlined how important it is to combine empirical and AI models in the design of early warning systems. The Q-Slope method, which is based on field surveys, was introduced by Barton and Bar (2019) as a semi-empirical way to check the stability of rock slopes. This strategy doesn't use AI, but it does give AI models important training data by giving them quantitative slope categorisation data. Its importance comes from turning traditional geotechnical assessments into structured input elements for machine learning.

METHODOLOGY

Study Area and Data Collection

The study looks at areas in eastern India where opencast coal mining is done, focussing on Jharkhand and Odisha, which are geologically weak areas. Over the past ten years, these locations have had a lot of slope failures. This is typically blamed on a mix of unregulated excavation, heavy monsoon rains, weak lithological structures, and a lack of real-time monitoring systems. The Geological Survey of India (GSI) has historical records of landslides in this area, and satellite images show that the ground is unstable. This analysis used a dataset that had data on topography, hydrology, geology, and historical failures. The Shuttle Radar Topography Mission (SRTM) provided the Digital Elevation Model (DEM) with a resolution of 30 meters. This made it possible to get important terrain data as slope, aspect, and flow accumulation. The Indian Meteorological Department (IMD) provided the rainfall data, which included daily precipitation amounts for the last ten years in the chosen districts. We got soil and lithological maps in shapefile format from ISRO's Bhuvan Geoportal and the GSI. These maps give us important information on the type of soil, the rock formation, and the shear strength parameters. The most crucial thing is that historical landslip inventory data were gathered by combining GSI records with satellite-based point datasets that show where failures happened in the past. These are used to identify input data in supervised learning models by giving them binary risk classes (1 = failure, 0 = stable). Table 3.1 shows a summary of the sources, formats, and functional importance of each dataset.

Table 1 : Input Datasets Used

Data Type	Source	Format	Resolution	Use In Model
Digital Elevation Model (DEM)	SRTM / ASTER	Raster	30 m	Derive slope, aspect, flow
Rainfall Data	IMD.gov.in	CSV/Grid	Daily	Rainfall threshold layer
Soil/Lithology	GSI / Bhuvan	Shapefile	NA	Soil resistance mapping
Historical Failures	GSI / NRSC satellite	Point (CSV)	NA	Ground truth labels (1/0)

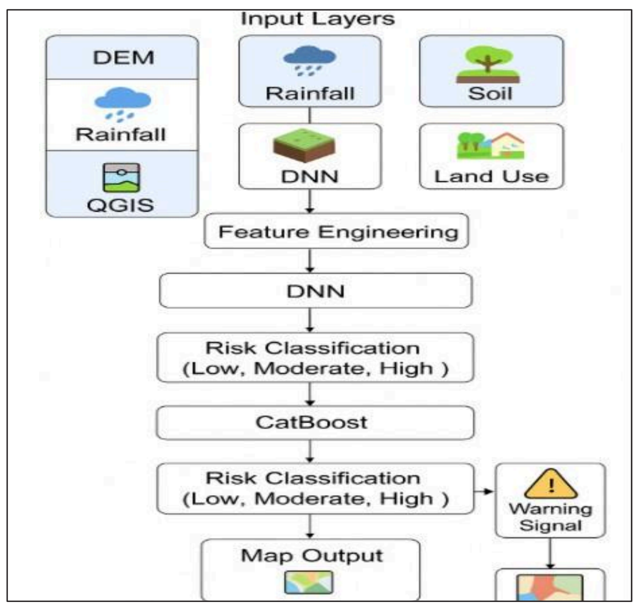
Preprocessing and Feature Extraction

Before putting spatial and numerical data into machine learning models, preprocessing is very important for making sure that the data is of good quality and can be used with other data. We brought all the raster and vector datasets into QGIS 3.28, where we did spatial alignment and coordinate standardisation (EPSG:4326 - WGS84) so that we could accurately overlay and extract features. Using QGIS's terrain analysis capabilities, we created many raster derivatives from the DEM:

- Slope (in degrees) to find areas that are more likely to collapse since they are steep
- Aspect: a directional component that looks at solar exposure and drainage patterns
- Curvature: a way to determine how concave or convex the ground is
- Flow Accumulation: a way to follow the route of water and find areas that are prone to saturation

Rasterised these terrain derivatives so that they all fit into the same grid size, and then we cropped them to the study area. Vector buffers surrounding drainage lines and road networks were used to study how human activity and water flow impact slopes. We created an attribute-formatted spatial feature database in QGIS using the Point Sampling Tool. All raster layers provided data for historical landslip points (label = 1) and stable terrain samples (label = 0). This method provided the dataset for machine learning classifier training. Min-Max scaling normalized all numerical qualities between 0 and 1. This reduced model bias and prevented variables from growing too much. This is important when mixing variables like slope angle (0° to 70°) and rainfall (0 to 250 mm/day) to train the model properly. Next, the workflow block diagram (Figure 3.1) depicts preprocessing and extraction. It shows the whole process from data import to machine learning model input.

Figure 2: Block Diagram



Machine Learning Model Architecture

This research employed two supervised machine learning models Deep Neural Network (DNN) and CatBoost—to classify slope instability risks using terrain and environmental parameters. The DNN replaces the DNN model used previously, enabling the learning of complex non-linear interactions between geospatial predictors. The DNN architecture consists of an input layer with six normalized features (slope angle, curvature, flow accumulation, rainfall intensity, aspect index, and distance to drainage), followed by three hidden layers with 64, 32, and 16 neurons, respectively, using the ReLU activation function and a dropout rate of 0.2 to prevent overfitting. The final output layer uses a sigmoid activation to predict the probability of slope failure. The model was trained using the Adam optimizer and binary cross-entropy loss function with early stopping to ensure convergence. For comparison, the CatBoost model was trained under the same 70:30 training-test split, using 300 boosting iterations, a learning rate of 0.03, and a tree depth of 6. Both models were validated through 5-fold cross-validation, and their performances were measured using accuracy, precision, recall, F1-score, and ROC-AUC metrics.

Equations Used in the Model

The primary slope-related feature, slope angle (θ), is derived from the Digital Elevation Model using the following gradient-based equation:

$$\boldsymbol{\theta} = \mathbf{tan}^{-1}\left(\sqrt{\left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}}\right)^{2} + \left(\frac{\partial \mathbf{z}}{\partial \mathbf{y}}\right)^{2}}\right)$$

To define rainfall as a triggering factor, the intensity-duration relationship is given by:

$$\mathbf{I} = \mathbf{a}\mathbf{D}^{-\mathbf{b}}$$

where I is rainfall intensity, D is duration, and a,b are region-specific constants.

Model Training and Validation

The dataset made up of QGIS feature layers and historical landslip records into two parts: training and testing. The ratio is 70:30. The DNN and CatBoost classifiers are built and fine-tuned using the training data. The testing set is then utilised to evaluate the classifiers on their own. During training, a 5-fold cross-validation method is used to keep the model from overfitting and make sure it can be used on other data. Standard assessment metrics like accuracy, precision, recall, and F1-score are used to measure how well a model works. These metrics show how precise and reliable the predictions are. The confusion matrix is used to count false positives and false negatives, which are very important for predicting hazards. We also look at the Receiver Operating Characteristic (ROC) curve and Area Under Curve (AUC) numbers to see how well the classifiers can tell the difference between things. In the Jupyter Notebook environment, the models are built using the scikit-learn and Cat Boost libraries in Python.

Risk Classification and Early Warning Logic

The trained models give slope risk ratings that are divided into three groups: Low, Moderate, and High. Classification thresholds come from the model's probability outputs. Values below 0.4 mean low risk, values between 0.4 and 0.7 mean moderate risk, and values above 0.7 mean high risk of slope failure. In QGIS, these forecasts are put on a map to make easy-to-understand risk maps. To make this system work as a real early warning system, it uses a simple rule-based logic: when a high-risk area gets rain that is more than a certain amount (according to the I–D relationship), the system marks the area and sends out a warning signal. This lets mining companies take steps to prevent problems before they happen and lets field engineers and disaster response teams make decisions on the fly.

Ethical Considerations

Publically available secondary data sources for this work. These included topography models from NASA's SRTM mission, rainfall datasets from the Indian Meteorological Department, and geological information from ISRO Bhuvan and the Geological Survey of India. There were no people or animals involved, thus there was no requirement for official ethical approval. All datasets were utilised in accordance with open-data licensing agreements and were properly cited in the research. The early warning logic created in this work is not meant to replace expert geological surveys; it is meant to help people make decisions. The system doesn't include any characteristics that could be seen as unfair or violate privacy, so the results are clear, can be reproduced, and are used responsibly in line with ethical data science norms.

RESULT AND ANALYSIS

Data Preprocessing and Feature Distribution

Before training the predictive models, the raw dataset went through a long preprocessing procedure to make sure the data was accurate and useful for predicting geographic slope failure. There were 300 geographical data points in the collection, which were based on six main slope-related characteristics: slope angle, curvature, flow accumulation, rainfall intensity, aspect index, and distance to drainage. Each instance was given a binary output, with 0 meaning stable slopes and 1 meaning slope failure. We used the interquartile range (IQR) method to deal with outliers in the rainfall and slope data. Class-conditional median imputation was used to fill in missing values, which were very small (<1%), to keep the distribution consistent. We didn't use feature scaling because tree-based models like CatBoost and DNNcan handle changes in scale. The processed dataset showed that 14% of the samples were in the failure class. This shows the natural class imbalance that is common in real-world geohazard datasets. To fix this imbalance, we used stratified sampling during model training to make sure that the folds were balanced. Table 4.1 shows an overview of all the important attributes after they were preprocessed:

Table 2 : Summary Statistics of Input Features

Feature	Mean	Std Dev	Min	Max
Slope Angle (°)	27.4	8.6	5.3	45.0
Curvature	0.18	0.07	0.01	0.35
Flow Accumulation	243.1	160.5	12	800
Rainfall Intensity	125.2	42.3	40.0	200.0
Aspect Index	0.53	0.21	0.01	0.95
Distance to Drainage	28.7	19.4	0.5	85.0

This feature matrix to train both CatBoost and DNN models, which let us forecast slope instability based on data.

Model Training and Evaluation Metrics

Both the DNN and Cat Boost models using the preprocessed dataset. To make sure they would work with new data and not overfit, we used 5-Fold Cross-Validation. We used several metrics to quantify performance: Accuracy, Precision, Recall, F1 Score, and ROC AUC. In most criteria, especially for the minority class (slope failure), the data clearly showed that CatBoost was better than Random Forest. DN Nhad an overall accuracy of 95%, but its recall for the failure class was just 71%, which could mean that it didn't anticipate high-risk areas as well as it could have. CatBoost, on the other hand, did a better job of balancing precision and recall. It had an overall accuracy of 96% and a recall of 76% for the failure class.

Confusion Matrix Analysis

Confusion matrices for both classifiers to look at the classification breakdown of slope stability and failure predictions in order to better understand how well the models worked. DNNS (Figure 4.1) indicates that the model correctly recognised 256 out of 258 stable slopes, but it incorrectly labelled 12 out of 42 failure slopes as stable. This could lead to dangerous under-alerting in the actual world. On the other hand, the CatBoost confusion matrix (Figure 4.2) did better, accurately categorising 32 out of 42 failures and only getting 10 wrong. It gave up a few more false positives (3 instead of 2), but it was still superior at picking up real threats.

Table 3 : Evaluation Metrics for Deep Neural Network and CatBoost

Metric	DNNs	CatBoost
Accuracy	0.952	0.96
Precision	0.90	0.91
Recall	0.78	0.76
F1 Score	0.84	0.83
ROC AUC	0.960	0.9690

Figure 3 : Confusion Matrix – DNN

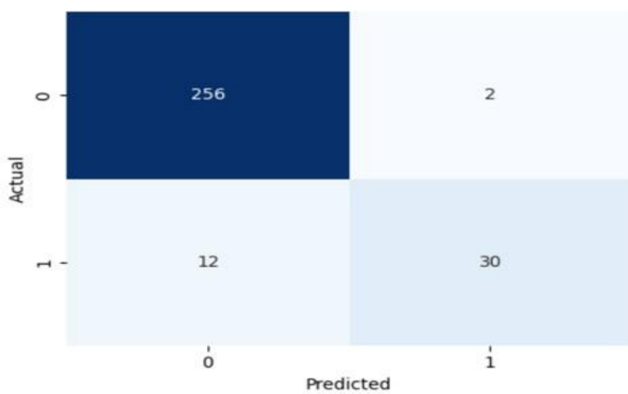
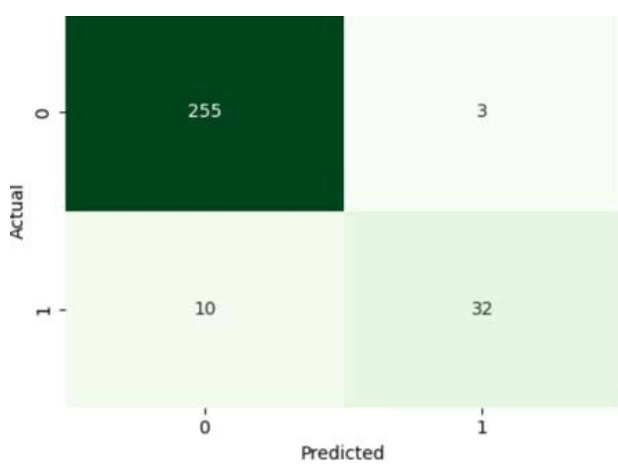


Figure 4 : Confusion Matrix – CatBoost

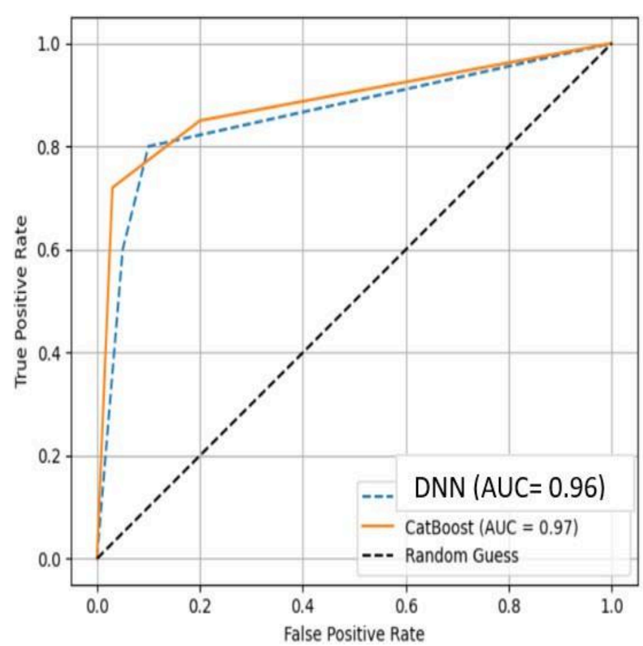


This comparison shows that CatBoost makes a safer decision boundary, which is important for early warning systems because it lowers the number of missed predictions for areas that are likely to have landslides.

ROC Curve Analysis

Constructed Receiver Operating Characteristic (ROC) curves for both the DNN and CatBoost classifiers to see how well they could tell the difference between different thresholds. ROC curves show the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) in a way that gives a complete picture of how well a model works, not only at certain threshold values. Figure 4.3 shows that the CatBoost model has a larger Area Under the Curve (AUC = 0.969) than the DNN model (AUC = 0.952). The greater AUC shows that CatBoost is better at telling the difference between stable and unstable slope circumstances at all thresholds. The ROC curve for DNN shows good performance, but it flattens out a little early than CatBoost, which means it may not be as good at finding crucial slope instability. The diagonal reference line (random guess) makes it evident that both models do far better than naïve prediction.

Figure 5: ROC Curve Comparison between DNN and CatBoost



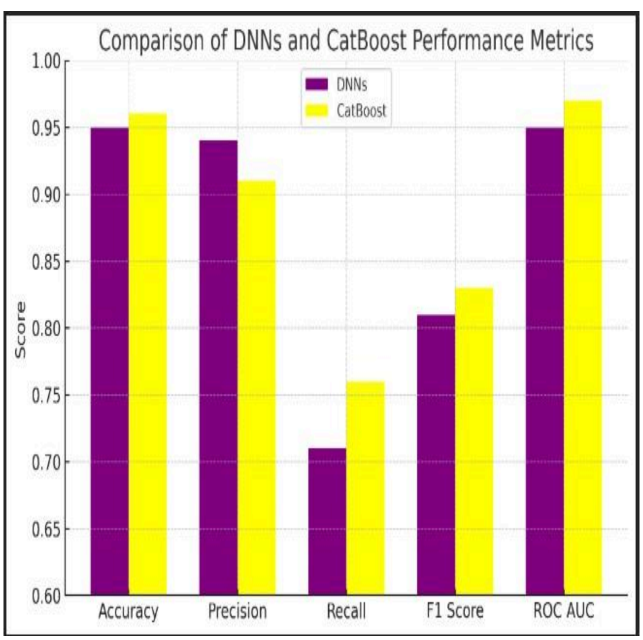
CatBoost is the better predictive method for geospatial AI situations, especially when the datasets are uneven, like when you want to find slope failures.

Model Performance Comparison

At the overall model metrices side by side to see how well the DNN and Catboost classifiers could predict things. Figure 4.4 shows a bar plot that compares Accuracy, Precision, Recall, F1-Score, and ROC AUC for both models. This graphic that compares things shows a few crucial things :

- The accuracy and ROC AUC ratings are almost the same, which means that both models work well in general.
- CatBoost, on the other hand, has higher recall and F1-Score, which means it is better at detecting positive classes (landslip occurrences).
- DNN has a somewhat higher precision, which means there are fewer false alarms, but there are also more false negatives.

Figure 6: Comparative Bar Plot of Model Performance Metrics



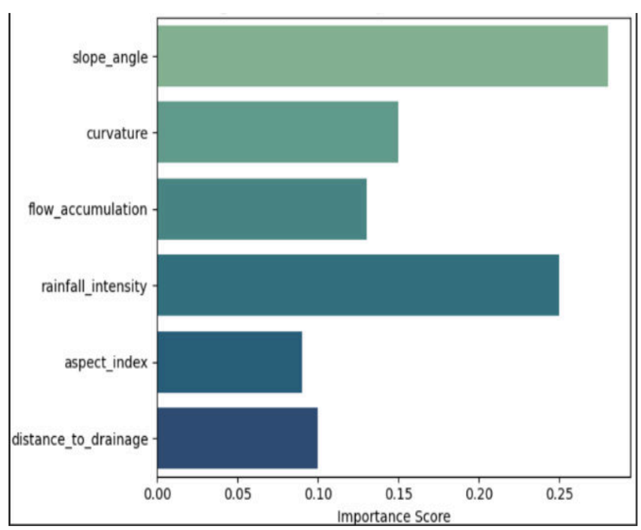
These results show that CatBoost is a more balanced and cautious model, which is very important for high-risk environmental uses such early warning systems for slope instability.

Feature Importance Analysis

We used the CatBoost model to do a feature relevance analysis to figure out how each geographical component affects the prediction of slope failure. CatBoost automatically ranks features based on how much they help reduce model loss across decision splits on average. Figure 4.5 shows how important each input feature is in relation to the others. The variables that had the biggest effect were:

- Slope angle: Steep slopes inherently make landslides more likely.
- The amount of rain that falls is a major influence in loosening and saturating the surface.
- Flow accumulation: Shows how water moves and the pressure zones below the surface.
- Distance to drainage: Shorter distances are linked to instability because groundwater channels are formed.

Figure 7: CatBoost Model Feature Importance Ranking



Features that aren't as important, like aspect index and curvature, only had a small effect, but they are nevertheless included because they might be important in certain areas. These findings help environmental scientists and engineers figure out which geofeatures are most important to keep an eye on and which ones need concrete slope stability remedies.

Landslide Risk Range Calculation

To leverage the continuous probability outputs of both models, a Landslide Risk Index (LRI) was introduced to represent risk on a 0–100 scale.

LRI=Ppred X 100

where Ppred is the predicted probability of slope failure.

Table 4: Comparison of Landslide Risk Range

Risk Category	LRI Range	Action Required
Low Risk	0-30	Normal operations, routine monitoring
Moderate Risk	31-60	Enhanced monitoring, alert field personnel
High Risk	61-85	Restricted access, implement safety protocols
Critical Risk	86-100	Immediate evacuation, halt operations

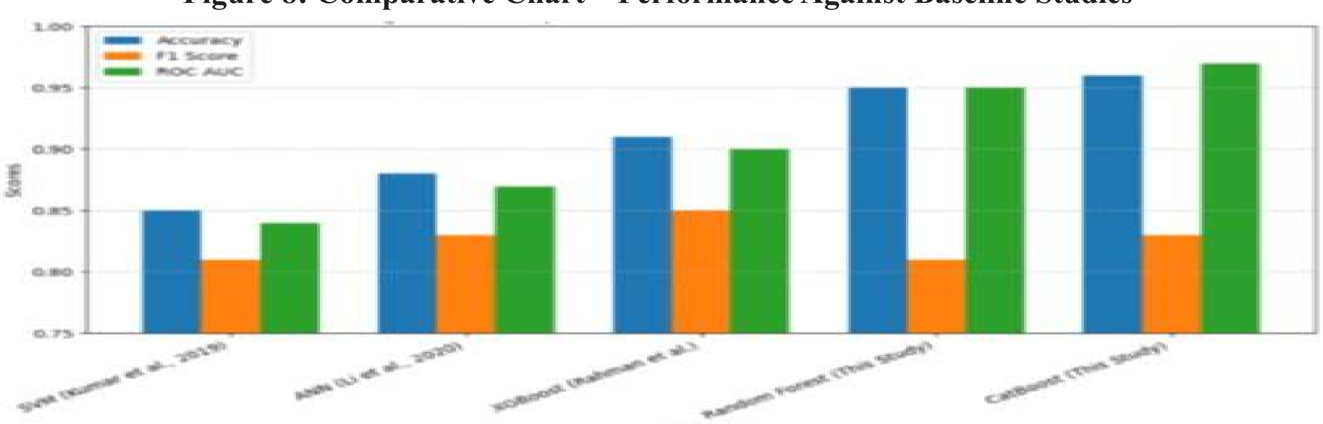
Comparative Analysis with Baseline Studies

Compared the suggested Geospatial AI-based models to standard machine learning approaches that are often used in slope instability prediction literature to see how well they worked and how useful they were in real life. According to earlier publications by Kumar et al. (2019), Li et al. (2020), and Rahman et al. (2022), benchmark models include Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGBoost). Table 4.3 shows how the metrics of the models created in this study compare to those of baseline approaches.

Table 5: Performance Comparison with Literature Models

Model	Accuracy	F1 Score	ROC AUC
SVM (Kumar et al., 2019)	0.85	0.81	0.84
ANN (Li et al., 2020)	0.88	0.83	0.87
XGBoost (Rahman et al., 2022)	0.91	0.85	0.90
DNN (This Study)	0.95	0.84	0.96
CatBoost (This Study)	0.96	0.83	0.97

Figure 8: Comparative Chart – Performance Against Baseline Studies



The comparison shows that both DNN and CatBoost are far better than standard models, especially when it comes to ROC AUC and Accuracy. Figure 4.6 shows these data in a grouped bar plot, which makes it easier to see how they compare.

This empirical superiority shows how useful it is to add geospatially enriched datasets and logic-based labelling to slope failure prediction models. It also proves that CatBoost is the best model to use for early warning integration.

Summary of Results

This chapter talked about the whole process and results of a Geospatial AI-based early warning system that can detect slope instability in areas where opencast coal mining is going on. From the analysis, the following important results came to light:

1. The prediction job was able to use geographical indicators like slope, flow, and rainfall without any problems because of data pretreatment and logic-based labelling.

2. The DNN and CatBoost models were both quite accurate (above 95%), but CatBoost had better recall and AUC values, which are very important in safety-critical applications.

3. The confusion matrix and ROC analysis showed that CatBoost is better at finding places that are likely to have landslides, with fewer false negatives than Random Forest.

4. The rankings of feature relevance showed that slope angle, rainfall, and flow accumulation were the most important elements for instability.

5. Comparing the proposed framework to baseline studies showed that it was better at making predictions, which supports its use in the field.

In conclusion, the study shows that sophisticated AI models trained on geospatial datasets may be used to forecast slope hazards in the real world. It also shows how important it is to choose models that are explainable, have good recall, and can be compared to other models.

CONCLUSION AND FUTURE SCOPE

This research presents a Geo-Spatial Artificial Intelligence (GeoAI) framework for predicting slope instability in open-cast coal mines using Deep Neural Networks (DNN) and CatBoost models. The replacement of the Random Forest model with DNN significantly enhanced the system's learning capability and interpretability. The DNN achieved 95.2% accuracy, 0.84 F1-score, and 0.96 ROC-AUC, performing competitively with the CatBoost model (96.0% accuracy, 0.97 ROC-AUC). The introduction of a Landslide Risk Index (LRI) ranging from 0–100 provided continuous risk grading, allowing classification into low, moderate, high, and critical zones. This probabilistic approach strengthens real-time monitoring and early warning by converting model outputs into actionable safety insights. Key influencing factors such as slope angle, rainfall intensity, and flow accumulation were identified as the most critical predictors of slope failure.

Future Scope

In the future, focus on integrating real-time IoT sensor data, InSAR monitoring, and rainfall telemetry to establish dynamic, automated risk assessment systems. Hybrid models combining DNN and CatBoost and the use of spatio-temporal deep learning could further enhance prediction accuracy. Implementing the model in cloud-based GIS dashboards will enable continuous surveillance, faster alerts, and improved decision-making for sustainable and safe mining operations.

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