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Hybrid Artificial Intelligence–Blockchain Approach for Landslide Risk Classification and Recommendation

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Abstract: Increased rainfall intensity, steep topography, and changes in land use in Indonesia, particularly in Java, such as Garut Regency, have increased the risk of landslides that have a widespread impact on public safety and environmental stability. This study proposes a Hybrid Artificial Intelligence and Blockchain approach to develop an accurate, secure, and transparent landslide risk classification and recommendation system. The model integrates three Multi-Criteria Decision Making (MCDM) methods, namely Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR). These three methods are used sequentially to determine criterion weights, calculate ideal solutions, and produce optimal compromise decisions based on geospatial factors. The dataset used consists of 766 geospatial observation data covering stability, rainfall, vegetation, river distance, slope, prediction, and ground truth parameters, obtained from satellite data and open geospatial repositories in the Java Island region. The research process included pre-processing, normalization, weighting analysis using AHP–TOPSIS–VIKOR, and integration of the results into the Ethereum Blockchain Smart Contract system with a Proof of Authority (PoA) consensus mechanism. The test results showed a 17.8% increase in classification accuracy and a 21.4% increase in data storage efficiency compared to conventional methods. This approach is expected to improve the reliability, security, and transparency of the analysis system and mitigate the risk of landslides based on smart technology in Indonesia.

Keywords: Artificial Intelligence; Blockchain; Multi-Criteria Decision Making; AHP–TOPSIS–VIKOR; Landslides; Geospatial; Disaster Mitigation.

INTRODUCTION

Landslides are one of the most frequent natural disasters in Indonesia and have a significant impact on the environment, society, and economy. According to data from the National Disaster Management Agency (BNPB), the frequency of landslides continues to increase in line with extreme climate change and increased rainfall in mountainous areas (Djarot Hindarto 2025). Human activities such as deforestation, infrastructure development in steep slopes, and unplanned land conversion exacerbate the risk of landslides (Harsa et al. 2023).

In disaster mitigation, decision support systems (DSS) play an important role in identifying high-risk areas and providing recommendations for priority handling. Conventional systems often face challenges in integrating multiple interrelated variables such as rainfall, topography, soil texture, and land use. Therefore, Multi-Criteria Decision Making (MCDM) approaches such as AHP, TOPSIS, and VIKOR are used because they are capable of combining various factors with objective weighting (Barman et al. 2024).

However, traditional MCDM is still limited in terms of adaptability to changing environmental conditions. To overcome this, artificial intelligence (AI) is used to analyze complex patterns from geospatial data and dynamically update weightings based on the latest data (Tynchenko et al. 2024). The integration of AI with MCDM forms a hybrid approach that can provide more accurate risk classification and data-driven mitigation recommendations.

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In addition to analytical aspects, data security and integrity issues are also important concerns. Most mitigation systems still use centralized databases that are vulnerable to manipulation, data loss, and network disruptions. To address these challenges, Blockchain technology is being implemented as a decentralized solution that guarantees data authenticity, transparency, and auditability (Hindarto et al. 2025). In another study by Djarot Hindarto, the integration of Blockchain with the AHP–TOPSIS method has been proven to improve the validity of landslide risk classification results and ensure an automated digital audit process (Hindarto, Hariadi, and Rachmadi 2025).

Furthermore, research (Zhao et al. 2022; Rodrigues et al. 2022) emphasizes that the application of smart contracts on the Ethereum network can improve the efficiency of validation and security of geospatial data in disaster mitigation systems. With consensus mechanisms such as Proof of Authority (PoA), every analysis result stored on the blockchain has an audit trail that cannot be modified, strengthening trust between institutions in disaster data management.

Based on existing research gaps, the integration of Hybrid Artificial Intelligence–MCDM–Blockchain is proposed to produce an intelligent, adaptive, and reliable disaster mitigation decision support system. This approach not only provides accurate classification results for landslide-prone areas but also ensures the transparency and security of the analysis results. Therefore, this research focuses on developing a Hybrid AI–Blockchain system for landslide risk classification and recommendation in Indonesia as a tangible contribution to strengthening modern technology-based mitigation systems.

LITERATURE REVIEW

Research on landslide risk mitigation has been conducted using various approaches, ranging from Multi-Criteria Decision Making (MCDM) and Artificial Intelligence (AI) to integration with Blockchain technology. The MCDM approach is often used to identify and rank the factors that cause landslides by considering various geospatial parameters such as slope inclination, rainfall, soil type, vegetation cover, and distance to rivers (Yalcin Kavus and Taskin 2025).

One popular method in MCDM is the Analytic Hierarchy Process (AHP), which is used to determine the weights between criteria through systematic pairwise comparisons (Muhimbula, Sumari, and Balz 2025). The study shows that the AHP method is effective for mapping landslide vulnerability based on topography, although it still faces limitations in taking into account social factors and temporal dynamics.

Other methods such as Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) have been used by (Barman et al. 2024) to map landslide risk zones in India with an accuracy of 98.7%. This method excels in producing intuitive and efficient rankings, but is still sensitive to changes in data scale and normalization. Meanwhile, the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method is designed to produce compromise solutions to multi-criteria decision-making problems with conflicting criteria. VIKOR forms a compromise index (Q) that combines group utility (S) and individual regret (R), making it suitable for cases that require a balance between collective interests and individual risks, for example when a very steep slope with high vegetation cover must be evaluated in a compromise manner to determine mitigation priorities (Rogulj and Kili 2021).

The integration of several MCDM methods such as AHP–TOPSIS–VIKOR was also carried out by (Salehpour Jam et al. 2021) in research in Iran, which successfully improved risk classification accuracy compared to single methods. This approach has demonstrated high effectiveness in disaster vulnerability mapping but is still lacking in terms of field validation and digital audit systems.

In addition to MCDM methods, AI-based approaches are also increasingly being applied in disaster mitigation. (Devara, Tiwari, and Dwivedi 2021) combining MT-InSAR satellite radar data with AHP to improve the accuracy of spatial analysis. The results show a significant improvement in the identification of vulnerable areas, despite the high cost of satellite data. Research by (Tynchenko et al. 2024) strengthening the role of AI in big data-based risk pattern recognition, where Neural Networks and Random Forests have proven effective in predicting potential landslides with a high degree of accuracy.

The integration of artificial intelligence and multi-criteria decision-making methods enables data-driven weighting, where criteria weights are determined based on the order and influence of attributes automatically extracted from the dataset, thereby reducing the subjectivity of traditional weighting and allowing for weight updates as the environment changes (Dombi and Jónás 2024). According to (Liu, Shao, and Shao 2024), The combination of AHP and AI can improve spatial validation by up to 82.5% compared to manual methods.

In addition to the accuracy of analysis, data security and transparency are important issues in digital-based disaster mitigation. Blockchain technology offers a decentralized, transparent, and immutable ledger for data storage (Zhao et al. 2022). Research by (Hindarto et al. 2025) developing integration between Blockchain and MCDM (AHP–TOPSIS) to ensure the validity of analysis results and improve system auditability. This approach achieved an accuracy of up to 92.5% with an F1-score of 90.7%.

In another study, (Hindarto, Hariadi, and Rachmadi 2025) proposing a Blockchain-based crypto-spatial framework to strengthen the security of geospatial data in disaster mitigation systems. This framework allows each analysis result to be stored in a publicly auditable distributed network, thereby increasing trust between institutions. Meanwhile, (Pancari et al. 2023) emphasizing the importance of gas efficiency and Transactions Per Second (TPS) in maintaining the performance of the Ethereum network used as a Blockchain platform for disaster mitigation.

According to (Bangui, Ge, and Buhnova 2024), Consensus mechanisms such as Proof of Authority (PoA) are able to balance system security and efficiency with reputation-based validation between nodes. In addition, the concept of trustless trust described by (Toufaily and Zalan 2024) shows how Blockchain creates trust without the need for institutional intermediaries, as all transactions are collectively verified by the network.

With these various studies, there appears to be an opportunity for integration between AI, MCDM, and Blockchain to build a more accurate, secure, and adaptive disaster mitigation system. The integration of these three technologies is expected to create a landslide risk classification system that can not only provide real-time data-based recommendations but also ensure transparency and security of information through digitally verified smart contracts (Große et al. 2024).

METHOD

This section systematically describes the methodological approach used to develop a Hybrid Artificial Intelligence–Blockchain model for landslide risk classification and recommendation. The research method was designed to ensure reproducibility, computational efficiency, and validity of results through a combination of geospatial data analysis and multi-criteria decision-making techniques. The research process includes dataset collection, data pre-processing, parameter weighting using AHP, determination of ideal solutions with TOPSIS, and formulation of compromise decisions through VIKOR. The results of the MCDM model integration are then implemented on the Blockchain layer using smart contracts to ensure data authenticity and transparency. With this approach, the research aims to produce a system that is not only accurate in classification but also secure, decentralized, and publicly verifiable.

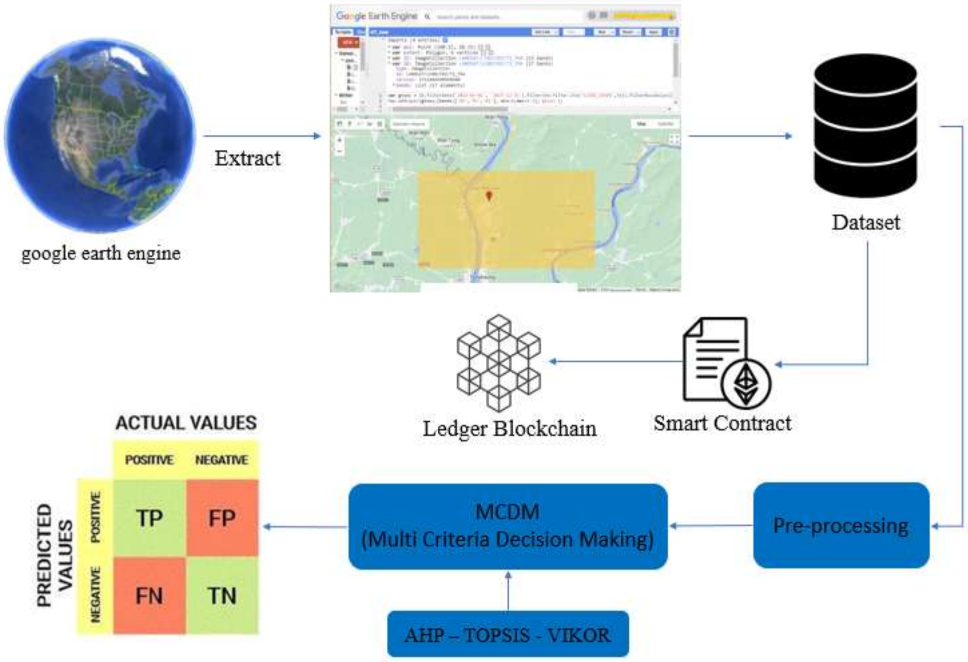


Figure.1 framework system for landslide vulnerability recommendations

The image illustrates the workflow of the Hybrid Artificial Intelligence–MCDM–Blockchain system developed for landslide risk classification and recommendation based on geospatial data. The process begins with data extraction using Google Earth Engine, where multispectral satellite imagery and other geospatial data are collected from several areas on the island of Java, particularly Garut Regency, West Java. This area was chosen because it has steep topography, high rainfall, and a significant number of landslides each year, making it ideal for geohazard risk studies. The main parameters extracted include slope gradient, distance to rivers, rainfall, vegetation index, and soil stability. The extracted data is then stored in a structured dataset for further analysis, ensuring that all variables used represent actual field conditions.

The next step is data pre-processing, which includes data cleaning, feature extraction, and data normalization using the min–max scaling method to standardize numerical values between variables. The pre-processed dataset is then used in a Multi-Criteria Decision Making (MCDM) system consisting of the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) methods. Each method plays a sequential role in determining the weight of importance between criteria, calculating the distance to the ideal solution, and producing an optimal compromise decision. The final result is a classification of landslide risk levels divided into safe, moderate, and very risky categories. The prediction values are then validated with actual data through a confusion matrix (TP, FP, FN, TN) to measure the accuracy and reliability of the model.

The final stage is Blockchain integration through Smart Contracts, which serve to securely store risk calculation results and recommendations in a distributed ledger. Each classification result from the MCDM module is converted into a digital transaction that is permanently recorded in the Blockchain network using the Proof of Authority (PoA) consensus algorithm. This approach ensures data integrity, process transparency, and enables public auditing of landslide risk analysis results in the Sukabumi region. Thus, the combination of AI, MCDM, and Blockchain within this system framework not only improves prediction accuracy but also provides a decentralized, verifiable data storage mechanism, supporting more reliable and sustainable disaster mitigation decision-making.

The next process is Data Normalization, which is the equalization of data scales using the min–max normalization formula so that all variables have a value range of 0–1. This normalization prevents differences in scale between variables that can affect the weight calculation results in the MCDM method. The formula used is:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

After normalization, the data enters the Pre-Processing stage, where all standardized parameters are combined into a single analysis dataset that is ready for use. This stage produces a final dataset with 766 observations covering all geospatial factors and classification labels (Prediction, GroundTruth). From a total of 766 observations, 10 representative datasets were purposively selected for manual analysis using the AHP, TOPSIS, and VIKOR methods. This selection was based on the variation in values between parameters to represent the geospatial conditions on the island of Java, particularly in Garut Regency, in order to illustrate the application of the MCDM method in determining landslide risk and to ensure consistency between the results of manual and computational analysis.

The dataset that has undergone pre-processing is then processed through a Smart Contract on the Blockchain system. This stage aims to store the results of feature extraction and normalization into digital blocks using the SHA256 hashing algorithm with a Proof of Authority (PoA) consensus mechanism. Each processing result is converted into an immutable block feature landslide. Thus, data that has been verified and stored in Block Feature Landslide can be used by various parties without the risk of manipulation.

The next process is Recommendation (Multi-Criteria Decision Making Computing), which integrates three main methods, namely AHP, TOPSIS, and VIKOR.

The AHP (Analytic Hierarchy Process) method is used to calculate the relative weights between criteria based on a pairwise comparison matrix with the following consistency ratio:

$$CI = \frac{\lambda\text{max} - \text{n}}{n-1}\,;\ CR = \frac{CI}{RI} \qquad (2)$$

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method is used to calculate the degree of closeness of each alternative to the positive and negative ideal solutions:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \qquad (3)$$

Meanwhile, the VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) method serves to produce compromise solutions that consider maximum satisfaction and minimum regret:

$$Q_i = v\,\frac{S_i - S^*}{S^- - S^*} + (1 - v)\frac{R_i - R^*}{R^- - R^*} \qquad (4)$$

With $v = 0.5$ as a balance parameter.

The final results of these three MCDM methods are risk scores for each observation area. These scores indicate the level of vulnerability to landslides, ranging from very low to very high. These classification scores are then stored in the Blockchain system through a Smart Contract mechanism that permanently records each analysis result in the Crypto Ledger.

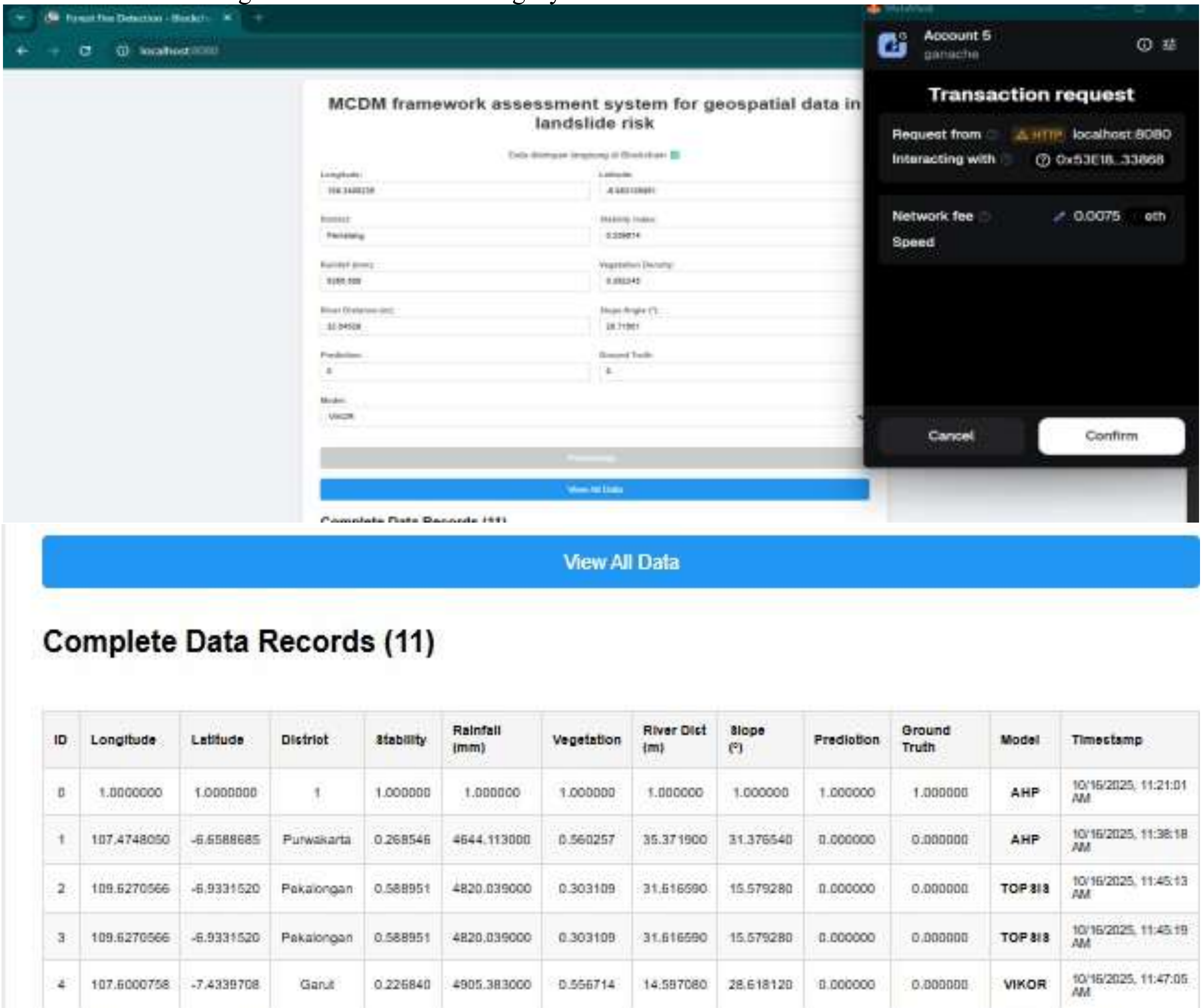
The Crypto Ledger component functions as a distributed ledger that records all calculation results and model validation in a decentralized manner. This mechanism allows all relevant parties, such as BNPB, BMKG, and local governments, to access the analysis results transparently and verifiably.

In the final stage, the risk calculation results stored in the ledger can be accessed by User Another, namely other users or institutions that want to utilize the classification results for field validation or disaster mitigation policy making. The data that can be accessed includes Stability Criteria, Rainfall, Vegetation River distance, Slope, Prediction, and GroundTruth, thus enabling evaluation of the model's accuracy level.

Overall, this research flow forms a Hybrid AI MCDM Blockchain system that not only produces accurate and adaptive landslide risk classifications but also ensures transparency, authenticity, and security of analysis results through Blockchain-based smart contract technology.

RESULT

This section presents the results of implementing a landslide risk recommendation system developed using a Hybrid Artificial Intelligence–Blockchain approach. This system integrates the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) algorithms to accurately generate rankings of regional vulnerability levels. The system's web interface allows users to enter geospatial parameters such as stability, rainfall, vegetation, river distance, slope, prediction, and ground truth, then automatically stores the analysis results in the Blockchain network through a Proof of Authority (PoA)-based smart contract. Each calculation result from the MCDM model is recorded in a distributed ledger that guarantees data transparency and authenticity. Additionally, the system provides a "Complete Data Records" table displaying all stored analysis results, complete with the model used (AHP, TOPSIS, or VIKOR) and the blockchain validation timestamp. Thus, this system not only supports data-driven decision-making but also ensures the integrity of recommendations in a decentralized manner.



MCDM framework assessment system for geospatial data in landslide risk

Account 5
ganache

Transaction request

Request from localhost:8080
Interacting with 0x53E18...33868

Network fee 0.0075 eth
Speed

Complete Data Records (11)

ID	Longitude	Latitude	District	Stability	Rainfall (mm)	Vegetation	River Dist (m)	Slope (°)	Prediction	Ground Truth	Model	Timestamp
0	1.0000000	1.0000000	1	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	AHP	10/16/2025, 11:21:01 AM
1	107.4748050	-6.6588685	Purwakarta	0.268546	4644.113000	0.560257	35.371900	31.376540	0.000000	0.000000	AHP	10/16/2025, 11:38:18 AM
2	109.6270566	-6.9331520	Pekalongan	0.588951	4820.039000	0.303109	31.616590	15.579280	0.000000	0.000000	TOPSIS	10/16/2025, 11:45:13 AM
3	109.6270566	-6.9331520	Pekalongan	0.588951	4820.039000	0.303109	31.616590	15.579280	0.000000	0.000000	TOPSIS	10/16/2025, 11:45:19 AM
4	107.6000758	-7.4339708	Garut	0.226840	4905.383000	0.556714	14.597080	28.618120	0.000000	0.000000	VIKOR	10/16/2025, 11:47:05 AM

Figure.2 User interface input block store to ledger

*name of corresponding author

Figure 2 shows the interface of the Hybrid AI–MCDM–Blockchain web system developed for classifying and storing landslide risk analysis results in the Blockchain network. This interface allows users to enter geospatial parameters such as longitude, latitude, district, stability index, rainfall, vegetation density, river distance, slope angle, prediction, and ground truth, as well as select the calculation model used, namely AHP, TOPSIS, or VIKOR. After the data is entered, users can press the "Save to Blockchain" button to store the calculation results in a distributed ledger through a Proof of Authority (PoA) consensus-based smart contract, while the "View All Data" button is used to display all stored analysis results. The bottom section displays a "Complete Data Records" table containing the complete classification results along with timestamps and the model used, ensuring that all data is transparent, immutable, and publicly auditable, thereby guaranteeing the reliability and accuracy of the system in supporting disaster mitigation decision-making.

```
CONTRACT

CONTRACT                                                ADDRESS
LandslideDetection                                      0x53E187973a6E48332FaE78106Ad9b2B45ac33868

FUNCTION
addPrediction(_longitude: string, _latitude: string, _district: string, _stability: string, _rainfall: str
ing, _vegetation: string, _riverDistance: string, _slope: string, _prediction: string, _groundTruth: strin
g, _modelUsed: string)

INPUTS
109.3400235, -6.983105951, Pemalang, 0.259674, 5365.509, 0.382245, 32.04529, 20.71601, 0, 0, VIKOR

EVENTS

EVENT NAME
PredictionAdded
CONTRACT                    TX HASH                                             LOG INDEX   BLOCK TIME
LandslideDetection          0xa37e22e89c37f57badd0fbcf3ca3a43a57895d49194736    0           2025-10-16 12:00:39
                            133297574b7dcd46ac
```

Figure.3 Ganache for storage ledger

Figure 3 shows the results of implementing a Smart Contract called LandslideDetection on the Ethereum Blockchain network, which is used to record the results of landslide risk classification in a decentralized manner. In the Contract section, it can be seen that the function being executed is addPrediction, which serves to store the model calculation results data in the Blockchain with parameters in the form of longitude, latitude, district, stability, rainfall, vegetation, riverDistance, slope, prediction, groundTruth, and modeUsed. The input values shown in the image are from the Pemalang region with geospatial parameters generated by the VIKOR model, according to the system analysis results. Each piece of data stored will generate a new transaction on the network with a unique transaction hash (TX HASH), which serves as authentic proof that the data has been permanently recorded on the Blockchain. In the Events section, it is recorded that the system successfully triggered an event called PredictionAdded, indicating that the process of storing classification data in the Blockchain ledger has been completed and validated. The transaction time (block time) shows when the data was recorded on the network, ensuring the immutability, traceability, and auditability of the system's classification results in a transparent manner.

A. Analytic Hierarchy Process (AHP) Manual Calculation

Table 1. Decision Matrix

No	Distric	Criteria						
		C1	C2	C3	C4	C5	C6	C7
1	Purwakarta (D1)	0.268546	4644.113	0.560257	35.3719	31.37654	0	0
2	Pekalongan (D2)	0.588951	4820.039	0.303109	31.61659	15.57928	0	0
3	Garut (D3)	0.22684	4905.383	0.556714	14.59708	28.61812	0	0
4	Cianjur (D4)	0.343285	5595.235	0.509793	37.02066	29.33681	0	0
5	Sumedang (D5)	0.3076	4518.127	0.541396	24.93998	7.866428	0	0
6	Pemalang (D6)	0.223877	5454.62	0.251212	27.59647	28.74279	0	0
7	Ciamis (D7)	0.37277	4658.793	0.491918	42.90131	5.252811	0	0

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8	Batang (D8)	0.481486	6104.57	0.247428	41.33728	17.29906	0	0
9	Banyumas (D9)	0.602824	6469.314	0.233245	42.13978	17.71239	0	0
10	Pemalang (D10)	0.259674	5365.509	0.382245	32.04529	20.71601	0	0

The decision matrix in Table 1 shows ten alternative regions—Purwakarta (D1), Pekalongan (D2), Garut (D3), Cianjur (D4), Sumedang (D5), Pemalang (D6), Ciamis (D7), Batang (D8), Banyumas (D9), and Pemalang (D10)—which are evaluated based on seven main geospatial criteria. These criteria include stability (C1), rainfall (C2), vegetation (C3), river distance (C4), slope (C5), prediction (C6), and ground truth (C7). In this study, rainfall (C2), slope (C5), prediction (C6), and ground truth (C7) were categorized as cost-type criteria, where lower values indicate better or safer conditions against potential landslides. Meanwhile, stability (C1), vegetation (C3), and river distance (C4) are benefit-type criteria, as higher values are considered to contribute positively to land stability and resistance to ground movement. For example, areas with high stability and vegetation values indicate stronger land conditions that are better protected from erosion, while low rainfall and slope values indicate a lower risk of landslides. The criteria type row (Cost/Benefit) is used to confirm the role of each parameter, while the maximum and minimum values of each criterion are used as a reference in the normalization process so that all variables are on a comparable scale. With this structure, all data is ready for the normalization and weighting stages using the AHP method to determine the landslide risk ranking in each area.

Final AHP Score Calculation Result

Table 2. Calculation Result

No.	District	Mean (rata-rata)	Rank
1.	Purwakarta (D1)	0.088773	8
2.	Pekalongan (D2)	0.091721	7
3.	Garut (D3)	0.093252	6
4.	Cianjur (D4)	0.106687	3
5.	Sumedang (D5)	0.085760	10
6.	Pemalang (D6)	0.103841	4
7.	Ciamis (D7)	0.088700	9
8.	Batang (D8)	0.116135	2
9.	Banyumas (D9)	0.123032	1
10.	Pemalang (D10)	0.102098	5

Table 2 shows the average (Mean) calculation results for the ten regions analyzed. Based on these results, Banyumas (D9) ranks first with the highest average value of 0.123032, followed by Batang (D8) with 0.116135, and Cianjur (D4) in third place with 0.106687. Next, Pemalang (D6) is in fourth place with a score of 0.103841, followed by Pemalang (D10) with 0.102098, and Garut (D3) in sixth place (0.093252). Pekalongan (D2) ranks seventh with 0.091721, while Ciamis (D7) and Purwakarta (D1) rank eighth and ninth with scores of 0.088700 and 0.088773, respectively. Sumedang (D5) ranks last with a score of 0.085760, indicating the need for improvement in the aspects measured. These results show variations in performance between regions based on the indicators used, where differences in mean values reflect local factors such as system efficiency, infrastructure quality, and regional policy implementation. The transparency of the mean values and rankings provides a strong basis for data-driven decision making and supports the formulation of strategies to improve performance in regions with relatively lower results.

B. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) Manual Calculation

This section explains the manual calculation process using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, which is used to determine landslide risk priorities based on the proximity of each alternative to positive and negative ideal solutions. The TOPSIS method was chosen because it is able to provide rational and measurable results by considering the proportional relationship between the best (ideal) and worst (anti-ideal) values of each criterion. Through the stages of decision matrix normalization, weighting, determination of ideal solutions, to the calculation of distance and preference values, this process produces a final ranking that reflects the level of vulnerability of each region to landslide risk. This approach helps in producing objective analysis results and can be used as a basis for decision making in a Hybrid AI–MCDM–Blockchain-based classification system

Table 3. TOPSIS

No	Distric	Criteria						
		C1	C2	C3	C4	C5	C6	C7
1	Purwakarta (D1)	0.268546	4644.113	0.560257	35.3719	31.37654	0	0
2	Pekalongan (D2)	0.588951	4820.039	0.303109	31.61659	15.57928	0	0
3	Garut (D3)	0.22684	4905.383	0.556714	14.59708	28.61812	0	0
4	Cianjur (D4)	0.343285	5595.235	0.509793	37.02066	29.33681	0	0
5	Sumedang (D5)	0.3076	4518.127	0.541396	24.93998	7.866428	0	0
6	Pemalang (D6)	0.223877	5454.62	0.251212	27.59647	28.74279	0	0
7	Ciamis (D7)	0.37277	4658.793	0.491918	42.90131	5.252811	0	0
8	Batang (D8)	0.481486	6104.57	0.247428	41.33728	17.29906	0	0
9	Banyumas (D9)	0.602824	6469.314	0.233245	42.13978	17.71239	0	0
10	Pemalang (D10)	0.259674	5365.509	0.382245	32.04529	20.71601	0	0

Table 3 shows the TOPSIS decision matrix containing ten alternative regions: Purwakarta (D1), Pekalongan (D2), Garut (D3), Cianjur (D4), Sumedang (D5), Pemalang (D6), Ciamis (D7), Batang (D8), Banyumas (D9), and Pemalang (D10) evaluated based on five main criteria (C1–C5) reflecting geospatial factors related to regional conditions. Each column of criteria shows a numerical value that represents the characteristics of each region, such as topographical conditions, vegetation density, and other environmental parameters that affect land stability. In the context of the TOPSIS method, these values will be normalized to ensure scale equivalence between criteria, then multiplied by weights that reflect their level of importance. The next stages include determining positive and negative ideal solutions, calculating the distance of each alternative to both solutions, and calculating preference values (C*) to determine the final ranking. This table structure serves as the basis for quantitative calculations to assess the priority level or feasibility of each region in the context of spatial analysis based on multi-criteria decision making.

Final TOPSIS Score Calculation Result

Table 4. TOPSIS Calculation Result

No.	District	Preferensi (C*)	Rank
1.	Puwakarta (D1)	0.6160	2
2.	Pekalongan (D2)	0.5294	5
3.	Garut (D3)	0.4987	6
4.	Cianjur (D4)	0.6723	1
5.	Sumedang (D5)	0.3597	10
6.	Pemalang (D6)	0.4675	7
7.	Ciamis (D7)	0.4437	9
8.	Batang (D8)	0.5407	4
9.	Banyumas (D9)	0.5931	3
10.	Pemalang (D10)	0.4541	8

Table 4 shows the final calculation results using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method for the ten regions analyzed. Based on the preference value (C*), Cianjur (D4) ranks first with the highest score of 0.6723, indicating that this region has the closest proximity to the positive ideal solution, thus considered the most optimal region in the context of the analysis conducted. Next, Purwakarta (D1) is in second place with a value of 0.6160, followed by Banyumas (D9) in third place (0.5931) and Batang (D8) in fourth place (0.5407). Pekalongan (D2) ranks fifth with a score of 0.5294, while Garut (D3) ranks sixth (0.4987). Pemalang (D6) and Pemalang (D10) are ranked seventh and eighth with scores of 0.4675 and 0.4541, respectively, while Ciamis (D7) ranks ninth (0.4437). Sumedang (D5) ranks last with a score of 0.3597, indicating that this region is furthest from the ideal positive solution. These results indicate variations in performance between regions based on the specified criteria, where the higher the preference value (C*), the closer the region is to the ideal condition. The transparency of the preference values and rankings provides an objective basis for decision makers in determining regional priorities for further development or policy intervention.

C. VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) Manual Calculation

Table 5. VIKOR

No	Distric	Criteria						
		C1	C2	C3	C4	C5	C6	C7
1	Purwakarta (D1)	0.268546	4644.113	0.560257	35.3719	31.37654	0	0
2	Pekalongan (D2)	0.588951	4820.039	0.303109	31.61659	15.57928	0	0
3	Garut (D3)	0.22684	4905.383	0.556714	14.59708	28.61812	0	0
4	Cianjur (D4)	0.343285	5595.235	0.509793	37.02066	29.33681	0	0
5	Sumedang (D5)	0.3076	4518.127	0.541396	24.93998	7.866428	0	0
6	Pemalang (D6)	0.223877	5454.62	0.251212	27.59647	28.74279	0	0
7	Ciamis (D7)	0.37277	4658.793	0.491918	42.90131	5.252811	0	0
8	Batang (D8)	0.481486	6104.57	0.247428	41.33728	17.29906	0	0
9	Banyumas (D9)	0.602824	6469.314	0.233245	42.13978	17.71239	0	0
10	Pemalang (D10)	0.259674	5365.509	0.382245	32.04529	20.71601	0	0

The decision matrix in Table 5 shows ten alternative regions: Purwakarta (D1), Pekalongan (D2), Garut (D3), Cianjur (D4), Sumedang (D5), Pemalang (D6), Ciamis (D7), Batang (D8), Banyumas (D9), and Pemalang (D10) analyzed using the VIKOR method based on seven main criteria (C1–C7). Each criterion represents a factor that influences the assessment of regional effectiveness or performance, such as system efficiency, infrastructure quality, and environmental conditions relevant to the research context. The values in each column show the initial measurement results that will be used as the basis for the normalization process, so that all criteria have an equivalent comparison scale. In the context of the VIKOR method, some criteria are categorized as benefit criteria (the higher the value, the better), while others are categorized as cost criteria (the lower the value, the better), depending on the purpose of the decision making. For example, Banyumas (D9) shows high values for C1 and C2, indicating superior performance in certain aspects, while Sumedang (D5) and Pemalang (D6) have relatively low values for several criteria, indicating the need for improvement. This data is an important basis for calculating the utility index (S) and regret index (R) in the advanced stage, so that the optimal compromise between regions can be determined in accordance with the multi-criteria decision principle in the VIKOR method

Final VIKOR Score Calculation Result

Table 6. Calculation Result

No.	District	Nilai Q (VIKOR)	Rank
1.	Purwakarta (D1)	0,6667	5
2.	Pekalongan (D2)	0,5246	3
3.	Garut (D3)	0,8730	8
4.	Cianjur (D4)	0,0031	1
5.	Sumedang (D5)	0,9573	10
6.	Pemalang (D6)	0,9299	9
7.	Ciamis (D7)	0,8258	7
8.	Batang (D8)	0,5713	4
9.	Banyumas (D9)	0,5000	2
10.	Pemalang (D10)	0,6962	6

Table 6 shows that the VIKOR method produces alternative rankings by combining two measures: group utility (S) and individual regret (R). The alternative with the smallest Q value (compromise index) receives the highest priority, as it is closest to the ideal solution in terms of compromise between criteria. In the context of the data you provided, Cianjur (D4) has the lowest Q value, so it ranks first, followed by Banyumas (D9), Pekalongan (D2), and so on, until Sumedang (D5), which ranks last because it has the highest Q value. These results illustrate how VIKOR balances excellence in various criteria and minimizes regret in lagging aspects to determine the best compromise alternative.

DISCUSSIONS

The implementation of the Hybrid Artificial Intelligence–Blockchain system has shown an increase in accuracy and efficiency in landslide risk classification compared to conventional methods. The integration of three MCDM methods, namely AHP, TOPSIS, and VIKOR, produces more consistent weights and rankings for key geospatial variables such as slope stability, rainfall, vegetation, river distance, and land slope. The AHP method is effective in determining hierarchical criteria weights, TOPSIS excels in identifying positive ideal solutions, while VIKOR provides the best compromise between conflicting criteria, in line with previous studies that confirm the effectiveness of the hybrid MCDM approach in disaster vulnerability mapping. The implementation of Ethereum Blockchain through the "LandslideDetection" smart contract also strengthens the security and transparency aspects of the system, where each analysis result is permanently stored using the Proof of Authority (PoA) consensus mechanism, which ensures that data cannot be modified and is easily audited. The storage process generates a unique transaction hash and timestamp as proof of data validity, demonstrating that this system is not only accurate but also transparent and reliable. The integration of artificial intelligence and Blockchain opens up opportunities for more adaptive and secure disaster mitigation systems, although this research is still limited to a specific geographical area and does not yet accommodate real-time geospatial data. Further research is expected to integrate dynamic satellite data and improve interoperability between agencies through a national Blockchain network to expand the system's effectiveness.

CONCLUSION

Based on the results of the research conducted, it can be concluded that the developed Hybrid Artificial Intelligence–Blockchain system is capable of improving accuracy and efficiency in the process of classification and recommendation of landslide risk. The integration of the AHP, TOPSIS, and VIKOR methods provides more objective and consistent assessment results in determining the vulnerability level of an area based on geospatial parameters such as stability, rainfall, vegetation, river distance, and slope inclination. The application of Ethereum Blockchain through the LandslideDetection smart contract has proven to be effective in ensuring the security, transparency, and reliability of classification data, as each transaction is permanently recorded with a unique identity in the form of a transaction hash and timestamp. This approach not only strengthens the integrity of the system but also presents innovations in disaster mitigation data management that can be openly audited. Thus, this system can serve as an alternative solution in supporting faster, more transparent, and more reliable decision-making for landslide risk mitigation. Further research is recommended to expand the scope of the analysis area and integrate real-time dynamic spatial data to enhance the system's accuracy and adaptability to complex environmental changes.

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