Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 20 No. 20 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijim.v20i20.63187

PAPER

Mobile Edge AI Framework for Real-Time ESG Compliance Auditing through NLP and Blockchain Ledger Verification

Nur Alamzah[1] (✉), Mursalim Nohong[1], Hendragunawan Sardjan Thayf[1], Baginda Hamzah[1], Adel Abdulwadood Taher[2]

[1]Hasanuddin University, Makassar, Indonesia

[2]University of Baghdad, Baghdad, Iraq

alamzah@fe.unhas.ac.id

ABSTRACT

The Mobile Edge artificial intelligence (AI) framework is introduced as an environmental, social, and governance (ESG) verification system that integrates natural language processing (NLP) and permissioned blockchain to facilitate near-real-time ESG compliance auditing. A lightweight transformer model is employed to identify ESG-related claims and extract relevant indicators, numerical values, units, locations, and reporting times. Extracted claims are structured and recorded on the blockchain to ensure verifiable, tamper-resistant records. A discrepancy assessment mechanism then classifies each claim as supported, partially supported, contradictory, or unsupported. The prototype was evaluated using a synthetic Kaggle dataset containing 11,000 annual company records from 1,000 organizations across nine regions and multiple sectors. The ESG classification model achieved a true positive rate of approximately 93.2%, with F1-scores of 0.945, 0.915, and 0.895 for environmental, social, and governance claims, respectively. Claim verification rates ranged from 93.1% to 98.4%. Edge deployment reduced verification latency to 124 ms compared to 231 ms in the cloud environment, representing a 46.3% reduction. These findings indicate that the framework can enable proactive ESG auditing, enhance claim traceability, accelerate verification, and deliver explainable compliance-risk signals.

KEYWORDS

mobile edge artificial intelligence (AI), environmental, social, and governance (ESG) compliance, natural language processing (NLP), blockchain verification, real-time auditing

1 INTRODUCTION

Organizations disseminate sustainability information via annual reports, websites, advertisements, press releases, and social media platforms [1]. Recent regulatory initiatives, including the European Union's Corporate Sustainability Reporting Directive (CSRD), mandate that organizations within its jurisdiction disclose environmental and social impacts, risks, policies, and performance in accordance with standardized reporting requirements [2]. Despite these regulatory advancements,

Alamzah, N., Nohong, M., Thayf, H. S., Hamzah, B., Taher, A. A. (2026). Mobile Edge AI Framework for Real-Time ESG Compliance Auditing through NLP and Blockchain Ledger Verification. *International Journal of Interactive Mobile Technologies (iJIM)*, 20(20), pp. 108–121. https://doi.org/10.3991/ijim.v20i20.63187

Article submitted 2026-07-02. Revision uploaded 2026-08-18. Final acceptance 2026-08-20.

© 2026 by the authors of this article. Published under CC-BY.

discrepancies often persist between publicly reported environmental, social, and governance (ESG) claims and actual organizational performance. Corporate disclosures may be imprecise, lack sufficient supporting evidence, remain incomplete, or be overstated, which can mislead stakeholders and elevate the risk of greenwashing [3]. These inconsistencies may arise from human error, fragmented information systems, outdated records, inconsistent measurement methodologies, or insufficient coordination among sustainability, operations, and marketing departments.

Traditional ESG audits are generally periodic, manual, and retrospective, relying on document reviews, spreadsheets, interviews, sampled evidence, and professional judgment [4]. Consequently, discrepancies may remain undetected until after an ESG report or public statement has been released. Meanwhile, operational ESG data are distributed across enterprise resource planning (ERP), supply chain management (SCM), human resources, energy-management systems, and Internet of Things (IoT) devices. This fragmentation makes it difficult to connect public claims with timely and reliable supporting evidence. Natural language processing (NLP) can analyse large volumes of unstructured corporate information, identify environmental, social, and governance (ESG) statements, classify them into relevant categories, and extract indicators, quantities, targets, and reporting periods [5]. However, identifying a claim does not confirm its validity. For instance, NLP may detect the statement "carbon emissions decreased by 25%," but it cannot verify the reported reduction without access to reliable operational evidence.

Blockchain can strengthen this process by providing traceable and tamper-resistant records of ESG evidence. A permissioned blockchain can store timestamps, metric identifiers, hashes, reporting periods, and authorization information while keeping confidential operational data off-chain. Previous studies demonstrate its potential to improve ESG data traceability and sustainability reporting [6]. Nevertheless, blockchain preserves record integrity rather than guaranteeing the accuracy of the original data. Mobile Edge artificial intelligence (AI) provides an additional opportunity by performing NLP analysis closer to organizational data sources. Edge computing can reduce processing latency, limit unnecessary transmission of sensitive information, and support faster compliance assessment [7]. Lightweight NLP models could therefore screen draft ESG disclosures before publication. Previous research has primarily investigated NLP-based ESG analysis, blockchain-enabled reporting, and edge AI as distinct approaches. Few studies have integrated these technologies into a comprehensive preventive auditing framework that extracts ESG claims, links them to traceable operational evidence, identifies discrepancies, and flags compliance risks before disclosure [8].

A mobile edge AI framework is proposed for near-real-time ESG compliance auditing, utilizing NLP and permissioned blockchain verification. This framework identifies and classifies ESG claims, extracts measurable attributes such as indicators, values, units, and reporting periods, validates these against recorded operational evidence, and generates explainable alerts for unsupported or inconsistent claims [9]. The primary innovation is integrating semantic claim analysis, edge-based inference, and blockchain-supported verification within a preventive auditing workflow. The framework is designed to complement, rather than replace, professional auditors and compliance teams, with an initial focus on measurable indicators including emissions, energy, water, waste, and renewable energy use.

2 LITERATURE REVIEW

ESG reporting has become increasingly important to investors, regulators, and other stakeholders. However, concerns remain regarding the reliability and

comparability of ESG information, as different rating and measurement systems may produce divergent assessments of the same organization [3]. Mandatory sustainability reporting can improve transparency, provided that disclosed information is consistent, reliable, and verifiable [4]. AI is increasingly being applied to ESG reporting and auditing. AI-based systems can process large volumes of corporate data, identify anomalies, and reduce the burden of manual review [1]. They can also assist auditors in examining ESG evidence and detecting potential inconsistencies in sustainability disclosures [9]. These capabilities indicate a broader transition from periodic, retrospective auditing toward more continuous, data-driven compliance monitoring [10].

The usefulness of natural language processing is that most of the ESG information is available in most text-based documents, such as reports, text emails, websites, and press releases. All of this has been done using techniques from NLP to analyze the readability and structure of sustainability reports [11]. There are models of NLP specifically created for the industry to further enhance the process of ESG assessment according to the various reporting standards from industry sectors [12]. NLP models can locate ESG-related statements, recognize the ESG type, and separate values, dates, targets, and measurement units. Machine-learning methods have also been applied to study ESG performance, disclosure quality, climate risk, and corporate profitability [13]. Blockchain technology can make ESG records more traceable and reliable. It can store timestamps, data hashes, transaction details, and author information. So far, blockchain has been used in carbon-accountability systems for supply chains [2] and in ESG verification platforms to build trust in sustainability reporting [10].

Systems using smart contracts have also been suggested for energy and audit applications [13]. Blockchain helps ensure that validated records are not changed without notice and provides a strong audit trail. Recent studies have examined the integration of AI, blockchain, the Internet of Things (IoT), and data analytics for ESG management [14], [15]. These technologies have demonstrated potential to enhance sustainability monitoring, reporting, transaction management, and risk assessment [16]. ESG software platforms have been developed to facilitate sustainability reporting across various industries [6]. Additionally, recent reviews emphasize the increasing significance of AI and data analytics in sustainable financial reporting [17]. Despite these advancements, three key gaps persist. First, research on AI and NLP primarily analyses ESG disclosures without verifying these claims against operational evidence. Second, while blockchain research enhances data integrity and traceability, it offers limited semantic analysis of corporate disclosures. Third, few studies integrate edge AI, NLP, and permissioned blockchain into a unified, near-real-time ESG auditing framework.

3 PROPOSED METHODOLOGY

3.1 Mobile edge auditing framework

The proposed framework integrates Mobile Edge AI, NLP, and permissioned blockchain to enable near-real-time ESG compliance auditing (see Figure 1). The framework verifies whether ESG claims are substantiated by operational evidence through six distinct layers: data acquisition, edge pre-processing, ESG claim extraction, operational evidence retrieval, blockchain verification, and compliance decision support. ESG-related content is sourced from corporate disclosures and processed securely at the enterprise edge prior to publication [18, 19]. The pre-processing stage cleans and normalizes the text while preserving key verification attributes, including values, units, dates, locations, and reporting periods. Subsequently, the NLP layer identifies and extracts ESG claims for further verification.

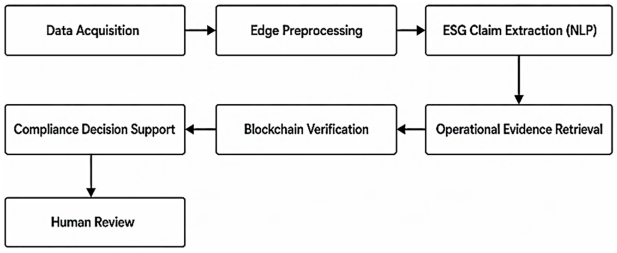


Fig. 1. Proposed mobile edge AI architecture for ESG claim verification

The fourth layer, Operational Evidence Retrieval, matches extracted ESG claims with relevant enterprise records using indicators, reporting periods, locations, business units, and measurement units. The fifth layer, Blockchain Verification, uses a permissioned blockchain to store hashes, timestamps, metric identifiers, and authorization records, while sensitive data remain off-chain. Retrieved evidence is hash-verified to detect alterations. Finally, the Compliance Decision and Alert layer compares claimed values with verified evidence and classifies each claim as Supported, Partially Supported, Unsupported, or Contradictory.

3.2 The ESG text input module

The ESG Text Input Module captures ESG-related content from draft and published corporate documents, with emphasis on screening disclosures before public release. Sources include sustainability and annual reports, websites, press releases, advertisements, investor communications, policy documents, and social media. Extracted claims are classified as Environmental (emissions, energy, water, waste, pollution), Social (worker safety, diversity, human rights, labor practices, community investment), or Governance (board structure, ethics, anti-corruption, regulatory compliance).

3.3 NLP claim-extraction model

The NLP claim-extraction model detects and filters out ESG-related statements and maps them to structured data to be checked against what is actually being done. Each input sentence is tokenized and represented as:

$$X = \{x_1, x_2, \ldots, x_n\} \tag{1}$$

where (x_i) represents the (ith) token and (n) is the total number of tokens in the sentence. The transformer encoder converts these tokens into contextual representations (2) and can be given as:

$$H = Transformer(X) \tag{2}$$

The contextual embedding of each token is inside where, which is represented by $\{h_1, h_2, \ldots, h_n\}$. To detect ESG claims, the sentence representation (h_{CLS}) can be passed through a fully connected layer, and then a softmax function (3) might be applied:

$$P(y \mid X) = \text{Softmax}(W_c h_{CLS} + b_c) \tag{3}$$

where (W_c) and (b_c) are trainable parameters, and (y) is the predicted class.
The predicted class (4) is calculated as:

$$\hat{y} = argmaxP(y_k \mid X) \tag{4}$$

where (k) represents the available ESG categories. A confidence threshold (τ) (5) is applied to uncertain predictions:

$$\text{Decision} = \begin{cases} \hat{y}, maxP(y_k \mid X) \geq \tau \\ Human\ Review, maxP(y_k \mid X) < \tau \end{cases} \tag{5}$$

Once the classification is done, the claims are classified as crucial attributes at the token level using the claim-level extraction module. The probability of assigning label (z_i) to token (x_i) (6) is expressed as:

$$P(z_i \mid x_i) = \text{Softmax}(W_e h_i + b_e) \tag{6}$$

The extracted ESG claim (7) is represented as:

$$C = \{c, i, v, u, t, l, d\} \tag{7}$$

where (c) is the ESG category, (i) is the indicator, (v) is the claimed value, (u) is the measurement unit, (t) is the reporting period, (l) is the location or business unit, and (d) is the direction of change.

The model is trained using a combined loss function (8) that can be given as:

$$L = \lambda_1 L_{cls} + \lambda_2 L_{ext} \tag{8}$$

where (L_{cls}) is the classification loss, (L_{ext}) is the token-extraction loss, and (λ_1) and (λ_2) control the contribution of each task.

3.4 Blockchain ledger design

This proposed architecture is based on a permissioned blockchain ledger that ensures the integrity, traceability, and provenance of operational ESG records. Each record (9) in the ESG is represented as:

$$R = \{ID, m, v, u, t, s, a, H(D)\} \tag{9}$$

where (ID) is a record's identifier; (m) is an ESG metric; (v) is the verified answer to the metric; (u) is the measurement unit; (t) is the reporting period; (s) is the data source; (a) is the entity authorized to report; and ($H(D)$) is the hash of the original operational data (D).

The hash value (10) is generated as:

$$h = H(D) \tag{10}$$

Retraction of operation record—a new hash (11) created to compare it with the stored hash of the blockchain:

$$V_b = \begin{cases} 1, H(D') = h \\ 0, H(D') \neq h \end{cases} \tag{11}$$

Retrieved operational record (D'). If ($V_b = 1$), then the record has not been modified since it was registered. If the value of $V_b = 0$, then the system detects that there may be an integrity violation and forwards the record to the next repository for further examination.

The ESG record, the time of the transaction (13), the name of the source (14), and the digital signature (15) may be put as:

$$T_j = \{R_j, TS_j, PK_j, SIG_j\} \tag{12}$$

This includes the ESG record where (R_j) is the ESG record, the timestamp (TS_j), the public key of the authorized participant (PK_j) and the digital signature (SIG_j).

3.5 Claim-to-evidence matching

The claim-to-evidence matching module connects the structured ESG claim retrieved by the NLP model with the operational record (determined from the blockchain ledger). An extracted claim (13) is represented as:

$$C = \{i_c, v_c, u_c, t_c, l_c\} \tag{13}$$

where (i_c) is the ESG indicator, (v_c) would be the value being claimed and (u_c) the unit of measurement, (t_c) the reporting period and (l_c) the location or business unit.

The operational evidence record (14) is represented as:

$$E_j = \{i_j, v_j, u_j, t_j, l_j\} \tag{14}$$

where (E_j) represents the (jth) record retrieved from the verified operational database.

The system calculates a similarity score between the extracted claim and each available evidence record (15) that can be given as:

$$M(C, E_j) = w_i S_i + w_t S_t + w_l S_l + w_u S_u \tag{15}$$

where (S_i), (S_t), (S_l) and (S_u) represent the similarity scores for the indicator, reporting period, location, and measurement unit. The weights satisfy (16):

$$w_i + w_t + w_l + w_u = 1 \tag{16}$$

The evidence record with the highest matching scores (17) is selected as:

$$E^* = \text{argmax} M(C, E_j) \tag{17}$$

A minimum threshold (θ) is used to determine whether the evidence is sufficiently relevant (18):

$$\text{Match Decision} = \begin{cases} E^*, M(C, E^*) \geq \theta \\ \text{No Reliable Match}, M(C, E^*) < \theta \end{cases} \tag{18}$$

When a suitable record is found, the claimed value is compared with the verified operational value. For numerical claims, the normalized discrepancy score (19) is calculated as:

$$D = \frac{|v_c - v_e|}{\max(|v_e|, \varepsilon)} \tag{19}$$

where (v_c) is the claimed value, (v_e) is the verified evidence value, and (ϵ) is a small constant used to prevent division by zero.

The verification result (20) is determined using predefined thresholds:

$$R = \begin{cases} \text{Supported}, D \leq \delta_1 \\ \text{Partially Supported}, \delta_1 < D \leq \delta_2 \\ \text{Contradictory}, D > \delta_2 \\ \text{Unsupported}, \text{No evidence is available} \end{cases} \tag{20}$$

where (δ_1) and (δ_2) are the lower and upper discrepancy thresholds.

3.6 Algorithm of the proposed framework

Input: ESG document (D), blockchain ledger (B), confidence threshold (τ), matching threshold (θ), and discrepancy thresholds (δ_1) and (δ_2)
Output: Verification status and risk level

1. *Start.*
2. *Divide document (D) into sentences* ($S = \{s_1, s_2, \ldots, s_n\}$)
3. *For each sentence* (s_i):
   - *Preprocess and tokenize the sentence.*
   - *Calculate the ESG claim probability* ($P(y_i | s_i)$).
4. *If* ($P(y_i | s_i) < \tau$):
   - *Mark the sentence as non-ESG or uncertain.*
   - *Continue to the next sentence.*
5. *Else:*
   - *Classify the claim as environmental, social, or governance.*
   - *Extract the indicator, value, unit, reporting period, and location.*
6. *Search the blockchain ledger for corresponding operational evidence.*
7. *If no evidence is found:*
   - *Set status as Unsupported.*
   - *Set risk level as High.*
8. *Else, verify the hash of the retrieved evidence.*
9. *If the retrieved hash does not match the stored hash:*
   - *Set status as Integrity Failure.*
   - *Set risk level as Critical.*
10. *Else, calculate the claim-to-evidence matching score (M(C,E)).*
11. *If* ($M(C,E) < \theta$):
    - *Set status as No Reliable Match.*
    - *Set risk level as High.*
12. *Else, calculate the discrepancy score*
13. *If* ($D \leq \delta_1$):
    - *Set status as Supported.*
    - *Set risk level as Low.*
14. *Else if* ($\delta_1 < D \leq \delta_2$):
    - *Set status as Partially Supported.*
    - *Set risk level as Medium.*
15. *Else:*
    - *Set status as Contradictory.*
    - *Set risk level as Critical.*
16. *Store the claim, matched evidence, discrepancy score, verification status, and risk level.*
17. *Generate an alert for high-risk or critical claims.*
18. *Generate the final ESG compliance report.*
19. *End.*

4 RESULTS AND DISCUSSION

The framework was evaluated using the publicly available ESG and Financial Performance Dataset from Kaggle, a synthetic dataset containing 11,000 company-year observations from 1,000 companies across nine industries and seven regions (2015–2025). The dataset contains 16 variables covering company characteristics, financial performance, ESG scores, and operational indicators, including carbon emissions, water use, and energy consumption. Growth Rate contains 1,000 missing values for the baseline year (2015). To minimize data leakage, the dataset was split at the company level, ensuring that all observations from each company remained within one partition. A 70:15:15 split produced 7,700 training, 1,650 validation, and 1,650 test observations. A lightweight transformer model was fine-tuned using a maximum sequence length of 128 tokens, AdamW optimization, a learning rate of 2×10^{-5}, a batch size of 32, and up to five epochs. Claim verification compared

extracted numerical values with reference values. Discrepancies ≤5% were classified as Supported, >5–15% as Partially Supported, and >15% as Contradictory. Claims lacking sufficient reference evidence were classified as unsupported. The dataset characteristics and experimental configuration are summarized in Table 1.

Table 1. Dataset and experimental configuration

Component	Experimental Details
Data source	ESG and Financial Performance Dataset
Dataset type	Synthetic annual company-level data
Dataset size	11,000 rows and 16 columns
Coverage	1,000 companies, nine industries, and seven regions
Study period	2015–2025
Main ESG variables	ESG overall, environmental, social, and governance scores
Operational evidence	Carbon emissions, water usage, and energy consumption
Missing values	1,000 unavailable GrowthRate values for 2015
Data split	70% training, 15% validation, and 15% testing by company
NLP model	Lightweight transformer with a maximum sequence length of 128
Blockchain type	Permissioned blockchain with SHA-256 record hashing
Decision thresholds	($\tau = 0.70$), ($\theta = 0.80$), ($\delta_1 = 0.05$), and ($\delta_2 = 0.15$)

Figure 2 presents the precision, recall, and F1-scores for the three ESG categories. Environmental achieved the highest performance (precision = 0.95, recall = 0.94, F1 = 0.945), followed by Social (0.92, 0.91, 0.915) and Governance (0.90, 0.89, 0.895), respectively.

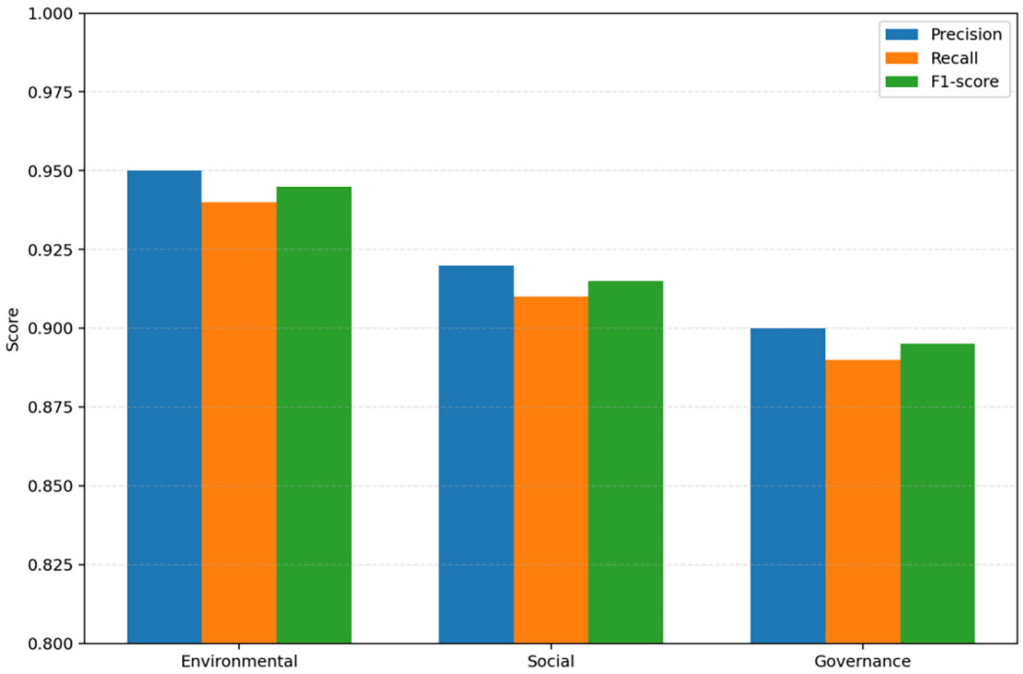


Fig. 2. ESG classification performance

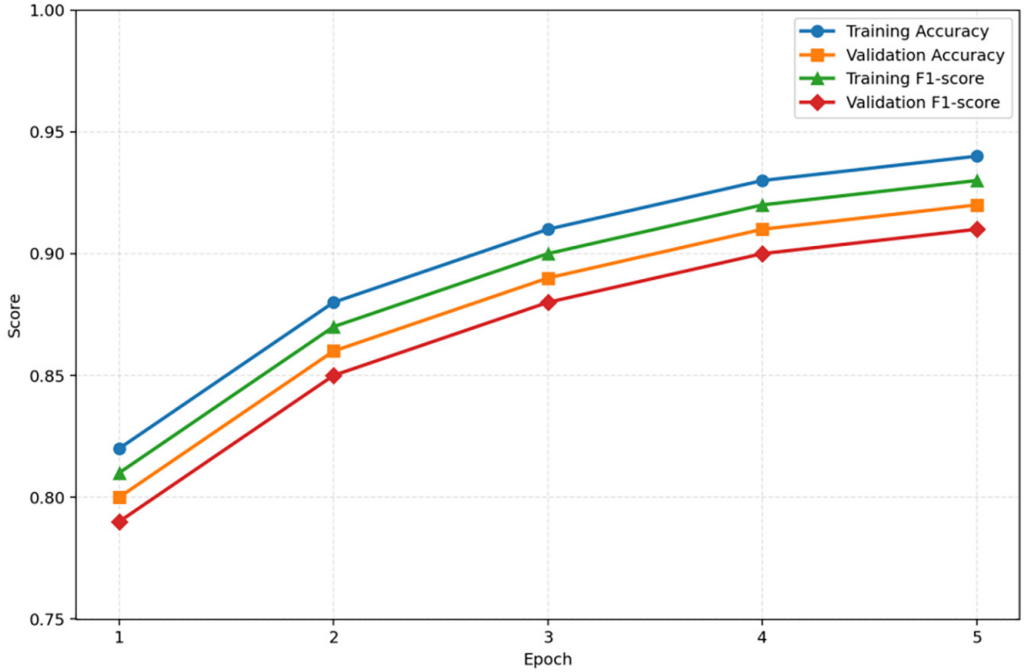


Fig. 3. Training and validation performance

Figure 3 shows stable model convergence, with final training and validation accuracies of 0.94 and 0.92, respectively, indicating limited overfitting.

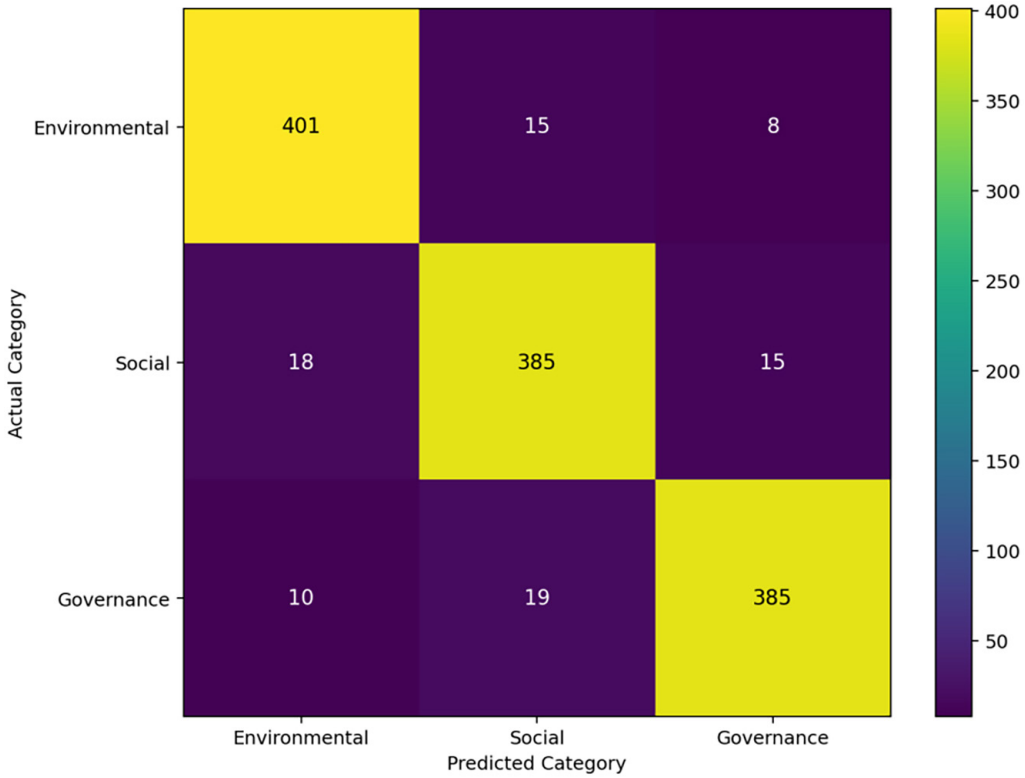


Fig. 4. ESG category confusion matrix

The confusion matrix for the task of classifying documents into the ESG categories is presented in Figure 4. Figure 4 shows 1,171 correct classifications out of 1,256 claims, corresponding to an overall accuracy of approximately 93.2%.

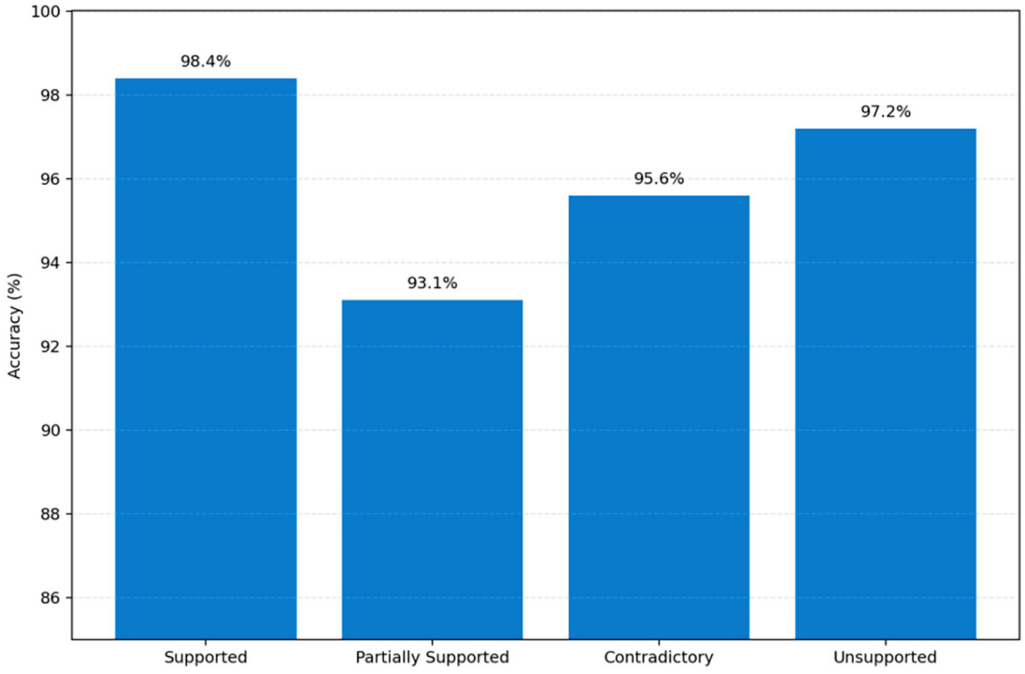


Fig. 5. Claim-verification accuracy

Data in the verification accuracy for various ESG claim conditions are shown in Figure 5, which shows verification accuracy ranging from 93.1% to 98.4%, with Supported claims achieving the highest accuracy and Partially Supported claims the lowest.

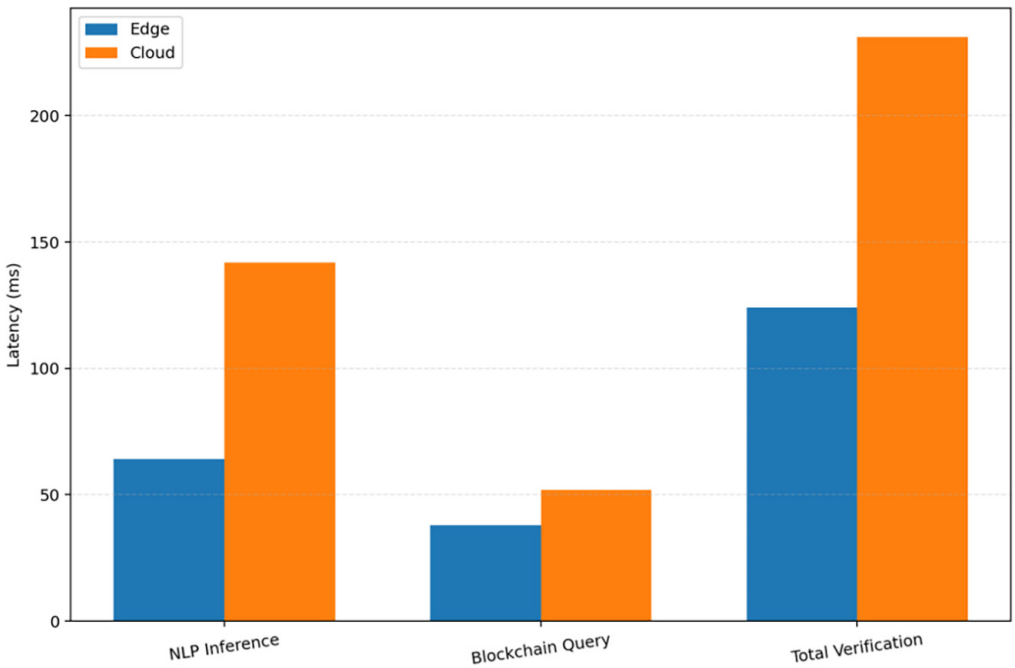


Fig. 6. Edge and cloud processing latency

Edge-based and cloud-based processing are compared, as shown in Figure 6, which compares edge and cloud processing latency. Total verification latency decreased from 231 ms in the cloud to 124 ms at the edge, representing a 46.3% reduction.

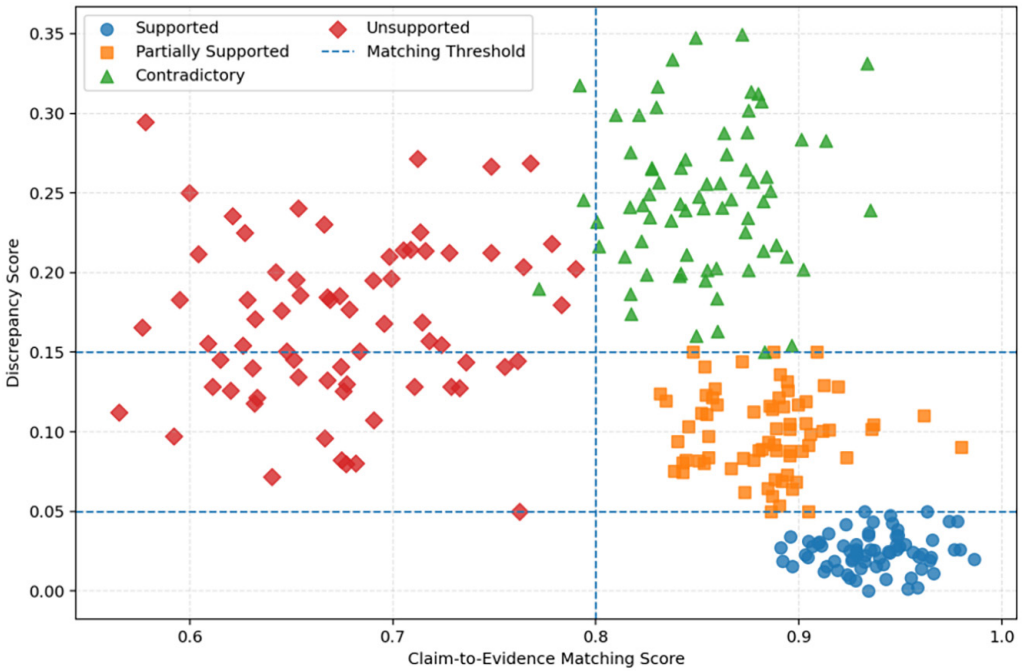


Fig. 7. Matching and discrepancy analysis

Figure 7 illustrates claim-to-evidence matching and discrepancy patterns. Supported claims generally exhibit high matching scores and discrepancies ≤0.05, while contradictory claims exceed the 0.15 discrepancy threshold.

5 DISCUSSION

The findings demonstrate the feasibility of integrating edge-based NLP with blockchain-supported evidence verification for ESG auditing. Environmental claims achieved stronger classification performance than social and governance claims, likely because environmental disclosures more frequently contain standardized quantitative indicators. The consistently high verification performance indicates that structured claim-to-evidence matching can support automated screening, while edge deployment substantially reduced verification latency. These results suggest that the framework is particularly suitable for preventive screening of ESG disclosures before publication.

6 CONCLUSION AND FUTURE SCOPE

This study proposed a Mobile Edge AI framework integrating NLP and permissioned blockchain for near-real-time ESG compliance auditing. The framework classifies environmental, social, and governance claims, extracts key attributes, and verifies them against blockchain-registered operational evidence. The prototype achieved approximately 93.2% ESG classification accuracy, 93.1–98.4% claim-verification accuracy, and reduced verification latency from 231 ms in the cloud

to 124 ms at the edge. The findings demonstrate the framework's potential to support faster, traceable, and preventive ESG verification. However, the evaluation used synthetic data, and blockchain ensures record integrity rather than the accuracy of source data. Future research should validate the framework using real corporate sustainability and operational data, extend multilingual and qualitative ESG analysis, and investigate federated learning and larger blockchain deployments.

7 DECLARATION

Ethics approval and consent to participate: This study did not require the approval of an ethics committee since we analyzed a secondary database.

7.1 Data availability statement

The study used the publicly available ESG & Financial Performance dataset available on Kaggle: https://www.kaggle.com/datasets/shriyashjagtap/esg-and-financial-performance-dataset

8 CONFLICT OF INTEREST

No potential conflict of interest was reported by the author(s).

9 REFERENCES

[1] E. M. Alotaibi and A. M. Alwathnani, "AI-enabled ESG compliance audit for stakeholders," *Sustainability*, vol. 17, no. 21, Art. no. 9513, 2025. https://doi.org/10.3390/su17219513

[2] E. M. B. Kuotian and S. K. Syed Ali, "Smartphone addiction and physical activity: Bibliometric analysis and systematic review," *JADHUR*, vol. 5, no. 2, pp. 1–20, 2026. https://doi.org/10.56868/jadhur.v5i2.348

[3] F. Berg, J. F. Kölbel, and R. Rigobon, "Aggregate confusion: The divergence of ESG ratings," *Rev. Financ.*, vol. 26, pp. 1315–1344, 2022. https://doi.org/10.1093/rof/rfac033

[4] H. B. Christensen, L. Hail, and C. Leuz, "Mandatory CSR and sustainability reporting: Economic analysis and literature review," *Rev. Account. Stud.*, vol. 26, pp. 1176–1248, 2021. https://doi.org/10.1007/s11142-021-09609-5

[5] V. D'Amato, R. D'Ecclesia, and S. Levantesi, "Firms' profitability and ESG score: A machine learning approach," *Appl. Stoch. Models Bus. Ind.*, vol. 40, pp. 243–261, 2023. https://doi.org/10.1002/asmb.2758

[6] P. Hąbek, "Evaluating ESG software solutions for sustainability reporting in the manufacturing sector," *Manag. Syst. Prod. Eng.*, vol. 33, pp. 420–432, 2025. https://doi.org/10.2478/mspe-2025-0041

[7] S. Ieva *et al.*, "Enabling next-generation digital transaction management platforms via artificial intelligence and blockchain," *Appl. Sci.*, vol. 16, no. 13, Art. no. 6697, 2026. https://doi.org/10.3390/app16136697

[8] J. Liu, Y. Yuan, and Z. Zhu, "The role of Artificial Intelligence in enhancing ESG disclosure quality in accounting," *J. Risk Financ. Manag.*, vol. 19, no. 1, Art. no. 58, 2026. https://doi.org/10.3390/jrfm19010058

[9] N. Li, M. Kim, J. Dai, and M. A. Vasarhelyi, "Using Artificial Intelligence in ESG assurance," *J. Emerg. Technol. Account.*, vol. 21, pp. 83–99, 2024. https://doi.org/10.2308/JETA-2022-054

[10] L. Liu, Z. Ma, Y. Zhou, M. Fan, and M. Han, "Trust in ESG reporting: The intelligent VeriGreen solution for incentivized verification," *Blockchain Res. Appl.*, vol. 5, Art. no. 100189, 2024. https://doi.org/10.1016/j.bcra.2024.100189

[11] H. Lee, J. H. Kim, and H. S. Jung, "ESG-KIBERT: A new paradigm in ESG evaluation using NLP and industry-specific customization," *Decis. Support Syst.*, vol. 193, Art. no. 114440, 2025. https://doi.org/10.1016/j.dss.2025.114440

[12] V. Rattanawiboonsom and N. Khan, "Blockchain technology in mobile payments: A systematic review of security enhancements in mobile commerce," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 21, pp. 134–148, 2024. https://doi.org/10.3991/ijim.v18i21.52099

[13] J. Okojie *et al.*, "Automated ESG reporting in energy projects using blockchain-driven smart compliance management systems," *Int. J. Multidiscip. Evol. Res.*, vol. 4, pp. 120–129, 2023. https://doi.org/10.54660/IJMER.2023.4.2.120-129

[14] J. K. Park, Y. M. Ahn, K. S. Ha, J. B. Lee, and G. Y. Yoo, "An AI-blockchain-integrated real options framework for sustainable infrastructure investment: Aligning profitability with ESG and UN SDGs," *Sustainability*, vol. 18, no. 10, Art. no. 4631, 2026. https://doi.org/10.3390/su18104631

[15] A. Saxena *et al.*, "Technologies empowered environmental, social, and governance: An industry 4.0 landscape," *Sustainability*, vol. 15, no. 1, Art. no. 309, 2023. https://doi.org/10.3390/su15010309

[16] N. Smeuninx, B. De Clerck, and W. Aerts, "Measuring the readability of sustainability reports: A corpus-based analysis through standard formulae and NLP," *Int. J. Bus. Commun.*, vol. 57, pp. 52–85, 2020. https://doi.org/10.1177/2329488416675456

[17] N. S. Sewpersadh, "Adaptive structural audit processes as shaped by emerging technologies," *Int. J. Account. Inf. Syst.*, vol. 56, Art. no. 100735, 2025. https://doi.org/10.1016/j.accinf.2025.100735

[18] Y. Wang and L. Wei, "Learner behavior recognition and dynamic guidance mechanism in interactive mobile simulation systems for vocational education," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 20, no. 6, pp. 25–38, 2026. https://doi.org/10.3991/ijim.v20i06.60865

[19] Q. Sun and X. Qiu, "How does green product certification affect ESG performance? Evidence from dual machine learning," *J. Clean. Prod.*, vol. 521, Art. no. 146201, 2025. https://doi.org/10.1016/j.jclepro.2025.146201

[20] K. K. Khotimah and Lusiana, "Live-streaming influencers and customer loyalty: A systematic review of customer satisfaction and service quality in TikTok commerce," *International Journal of Management Thinking*, vol. 4, no. 1, pp. 1–17, 2026. https://doi.org/10.56868/ijmt.v4i1.109

10 AUTHORS

Dr. Nur Alamzah, S.E., M.Si., is an academic, lecturer, and researcher at the Faculty of Economics and Business, Hasanuddin University (Unhas) in Makassar, Indonesia. He serves as the Head of the Master of Management Science Study Program (Ketua Program Studi Magister Sains Manajemen) at the Faculty of Economics and Business (FEB) Unhas (E-mail: alamzah@fe.unhas.ac.id).

Professor Dr. Mursalim Nohong is the Dean of Faculty of Economics and Business, Universitas Hasanuddin (UNHAS) Makassar, Sulawesi Selatan. He actively

delivers lectures and training in entrepreneurship, SME finance, green financial management, and public sector financial and asset management (E-mail: mursalim-nohong@fe.unhas.ac.id).

Dr. Hendragunawan Sardjan Thayf, S.E., M.Si., M.Phil., is a senior academic and lecturer in the Management Department at the Faculty of Economics and Business, Hasanuddin University (Unhas). He holds a doctorate from the Faculty of Philosophy at Gadjah Mada University (UGM), where he teaches and does research at Unhas. He specializes in corporate social responsibility, corporate governance, and business ethics (E-mail: hendragst@unhas.ac.id).

Baginda Hamzah, S.T., M.B.A., is an academic, entrepreneur, and lecturer in the Department of Management at the Faculty of Economics and Business, Hasanuddin University (Unhas). He is highly recognized for his dual career bridging corporate management, startup entrepreneurship, and academic teaching in South Sulawesi (E-mail: baginda.hamah@unhas.ac.id).

Assist. Prof. Dr. Adel Abdulwadood Taher is an Iraqi academic, author, and researcher who serves as an Assistant Professor in the Department of Public Administration at the University of Baghdad's College of Administration and Economics. He specializes in strategic management, public sector leadership, human resource management, and corporate foresight, frequently publishing peer-reviewed studies on organizational adaptation, soft-skills leadership, and administrative frameworks in state ministries (E-mail: adel.a@coadec.uobaghdad.edu.iq).