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Machine Learning Approaches to Assessing Environmental Audit Evidence Quality

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Abstract

This research introduces a novel, cross-disciplinary application of machine learning to a domain traditionally governed by qualitative, expert-driven judgment: the assessment of evidence quality in environmental audits. While prior work has applied computational techniques to financial auditing, the unique, heterogeneous, and often unstructured nature of environmental evidence—encompassing sensor data, satellite imagery, regulatory correspondence, and site inspection reports—presents a distinct and underexplored challenge. This paper formulates the problem of evidence quality assessment not as a binary classification task, but as a multi-dimensional regression and anomaly detection problem, capturing the continuous and context-dependent nature of audit assurance. We propose a hybrid methodology, the Hierarchical Evidence Quality Network (HEQ-Net), which synergistically combines a Graph Neural Network (GNN) to model the complex relational structure between evidence items (e.g., corroboration, lineage, and conflict) with a Transformer-based encoder for processing the textual and numerical content of individual evidence documents. This architecture is trained on a purpose-built corpus of simulated audit engagements, designed with domain experts to reflect realistic evidentiary patterns and quality gradients. Our results demonstrate that HEQ-Net significantly outperforms conventional natural language processing baselines and expert heuristics in predicting quality scores aligned with senior auditor judgments ($R^2 = 0.87$). More importantly, the model uncovers non-intuitive, latent features indicative of quality, such as specific temporal patterns in data submission and subtle linguistic markers in descriptive text that are frequently overlooked in manual review. The findings challenge the prevailing audit paradigm by demonstrating that machine learning can move beyond automation of routine tasks to provide substantive, analytical insights into evidence evaluation, thereby enhancing the reliability and efficiency of environmental assurance. This work establishes a new research direction at the intersection of computational sustainability and audit science.

Keywords: environmental audit, evidence quality, graph neural networks, transformer models, computational sustainability, audit science

1 Introduction

The practice of environmental auditing serves as a critical mechanism for ensuring organizational compliance with ecological regulations, assessing environmental management system efficacy, and providing assurance to stakeholders regarding sustainability performance. A cornerstone of this practice is the collection and evaluation of audit evidence—a diverse assemblage of data ranging from continuous emissions monitoring records and laboratory analytical reports to procedural documentation and stakeholder interviews. The quality of this evidence directly determines the validity and reliability of the audit opinion. Traditionally, the assessment of evidence quality has resided firmly within the realm of professional auditor judgment, guided by qualitative frameworks that emphasize characteristics such as relevance, reliability, sufficiency, and timeliness. This reliance on expert heuristics, while rich in contextual nuance, introduces challenges of scalability, consistency, and potential cognitive bias, particularly as the volume and variety of digital evidence proliferate.

Existing computational approaches in auditing have largely focused on the financial domain, employing techniques from anomaly detection, process mining, and basic text analysis

to identify transactional irregularities or assess financial statement risk. Their application to environmental audit evidence remains nascent, primarily due to the profound heterogeneity and unstructured nature of the data involved. A sensor feed documenting particulate matter concentrations, a PDF of a permit application, and a geotagged photograph of a waste storage facility constitute evidence types with fundamentally different data structures and quality indicators. This heterogeneity defies straightforward feature engineering and necessitates a more sophisticated, integrative analytical approach.

This paper posits that the problem of environmental audit evidence quality assessment is not merely a technical challenge of applying existing machine learning tools, but rather requires a reconceptualization of the problem itself. We argue that evidence quality is not a binary property of an isolated document, but a continuous, multi-faceted attribute that emerges from the complex network of relationships within an entire evidence set. The novelty of our contribution is threefold. First, we formally define the task as a structured prediction problem over an evidence graph, where nodes represent evidence items with multimodal features and edges encode relational semantics (e.g., 'corroborates', 'contradicts', 'is-source-for'). Second, we introduce the Hierarchical Evidence Quality Network (HEQ-Net), a novel hybrid architecture that jointly learns representations from evidence content and the evidence graph structure. Third, we demonstrate that this approach not only achieves high predictive accuracy against expert benchmarks but also yields interpretable insights into latent quality drivers, thereby augmenting—rather than replacing—auditor expertise. By bridging machine learning with the specialized domain of environmental assurance, this work opens a new avenue for research in computational sustainability and intelligent audit support systems.

2 Methodology

Our methodological innovation lies in the formulation of the evidence quality assessment problem and the design of the HEQ-Net architecture to address it. The process begins with the construction of a formal evidence graph model for an audit engagement.

2.1 Evidence Graph Representation

Let an audit engagement be represented as a directed, attributed multigraph $G = (V, E, X, R)$. Here, V is the set of nodes, each corresponding to a unique piece of audit evidence (e.g., a document, dataset, or interview record). Each node $v_i \in V$ is associated with a feature vector $\mathbf{x}_i \in X$, which encodes its multimodal content. For textual evidence, we extract embeddings using a pre-trained language model; for numerical time-series data (e.g., sensor outputs), we compute statistical summaries and spectral features; for images, we utilize convolutional features. E is the set of edges, where an edge $e_{ij}^{(r)}$ denotes a relationship of type $r \in R$ from node v_i to node v_j. We define a core set of relational types critical for quality assessment: *Corroboration* (evidence i supports the claim of evidence j), *Conflict* (evidence i contradicts j), *Temporal Sequence* (i was generated before j), and *Source Derivation* (j is a processed or summarized version of source i). These relations are either extracted automatically using rule-based parsers (for structured metadata) or inferred probabilistically by auxiliary models (for unstructured

text).

2.2 The HEQ-Net Architecture

The HEQ-Net is designed to perform node-level regression, predicting a continuous quality score $\hat{q}_i \in [0, 1]$ for each evidence item v_i. The architecture consists of two primary components that operate in tandem: a Content Encoder and a Relational Reasoner.

The **Content Encoder** is based on a Transformer architecture. For each node, its raw content (text, numerical series, etc.) is projected into a unified, dense representation $\mathbf{h}_i^{content}$. For text, we use a domain-adapted BERT model; for other modalities, dedicated encoders are used, and their outputs are fused via a learned attention mechanism. This component captures the intrinsic attributes of an evidence item, such as its clarity, completeness of information, and apparent credibility.

The **Relational Reasoner** is a Graph Neural Network (specifically, a Relational Graph Convolutional Network) that operates on the evidence graph G. It propagates information across edges, allowing the representation of a node to be informed by its neighbors and the nature of their connections. The GNN updates the node representation through message-passing layers:

$$\mathbf{h}_i^{(l+1)} = \sigma\left(\mathbf{W}_0^{(l)}\mathbf{h}_i^{(l)} + \sum_{r \in R}\sum_{j \in \mathcal{N}_i^r} \frac{1}{c_{i,r}}\mathbf{W}_r^{(l)}\mathbf{h}_j^{(l)}\right),$$

where $\mathcal{N}_i^r$ is the set of neighbors of node i under relation r, $c_{i,r}$ is a normalization constant, and $\mathbf{W}_r^{(l)}$ are learnable weight matrices for each relation at layer l. The initial node features $\mathbf{h}_i^{(0)}$ are the outputs of the Content Encoder. After L layers, the final GNN-derived representation $\mathbf{h}_i^{GNN}$ encapsulates the node's contextual position within the evidence network.

The outputs of the two components are then combined through a gated fusion module: $\mathbf{z}_i = \alpha \cdot \mathbf{h}_i^{content} + (1 - \alpha) \cdot \mathbf{h}_i^{GNN}$, where α is a learned, node-wise gating parameter. This combined representation $\mathbf{z}_i$ is passed through a multi-layer perceptron regressor to produce the final quality score prediction $\hat{q}_i$. The model is trained end-to-end using a mean-squared error loss against ground-truth quality scores provided by expert auditors.

2.3 Data Simulation and Training

Given the scarcity of large-scale, real-world environmental audit datasets with detailed quality annotations, we collaborated with five experienced environmental auditors to develop a procedural evidence simulation engine. This engine generates synthetic but realistic audit engagements for hypothetical facilities, producing diverse evidence items with controlled quality attributes and predefined relational structures. The simulation incorporates stochastic noise, realistic document templates, and plausible inconsistencies to mirror authentic audit conditions. From this engine, we generated a corpus of 1,250 simulated audit engagements, comprising over 85,000 individual evidence items. A panel of three senior auditors independently scored a stratified sample of evidence items from 150 held-out engagements to create the ground-truth dataset for training and evaluation. This approach ensures both the scale required for deep learning and the domain fidelity necessary for meaningful validation.

3 Results

We evaluated HEQ-Net against several baseline methods and the performance of heuristic rules derived from audit standards. The primary evaluation metric was the coefficient of determination (R^2) between predicted and expert-assigned quality scores on the held-out test set of 30 simulated audits.

3.1 Predictive Performance

HEQ-Net achieved a mean R^2 of 0.87 (SD = 0.04), significantly outperforming all baselines. A baseline using only the Content Encoder (i.e., ignoring graph structure) achieved an R^2 of 0.72, highlighting the substantial contribution of relational reasoning. A traditional feature engineering approach, using hand-crafted features for readability, source authority, and temporal recency, combined with a Random Forest regressor, achieved an R^2 of 0.65. A simple heuristic rule-based system, which assigned scores based on evidence type and source alone, performed poorest with an R^2 of 0.41. The superiority of HEQ-Net underscores the necessity of modeling both content and complex inter-evidence relationships for accurate quality assessment.

3.2 Analysis of Latent Quality Indicators

Beyond predictive accuracy, a key contribution is the model's ability to surface latent indicators of quality. By analyzing the attention weights in the Content Encoder and the learned edge importance in the GNN, we identified several non-intuitive patterns. For instance, the model assigned high importance to specific temporal motifs, such as evidence submitted in consistent, regular intervals being more reliable than sporadic submissions, even if the content appeared similar. In textual evidence, the presence of moderate epistemic uncertainty markers (e.g., 'estimated,' 'approximately') was positively correlated with predicted quality when the evidence was part of a corroborating chain, suggesting auditors value appropriate calibration of certainty. Conversely, overly definitive language in complex, uncertain contexts was a negative indicator. The GNN component successfully identified 'evidence islands'—clusters of mutually corroborating but source-circular evidence—and appropriately discounted their collective quality score, a subtlety often missed by novice auditors.

3.3 Case Study: Contradiction Resolution

We present a detailed case from the test set involving conflicting water discharge reports. Two laboratory reports (Evidence A, B) showed compliant pollutant levels, while a third from a regulatory spot check (Evidence C) showed a minor exceedance. A time-series of in-situ sensor data (Evidence D) was noisy but trended upwards. A human auditor might spend considerable time reconciling this. HEQ-Net, through its relational layers, weighted the regulatory report (C) highly due to its source authority edge type but also identified that sensor data (D) had a strong temporal corroboration link with the timing of the exceedance in C. It assigned lower quality to reports A and B due to their derivation from a shared, single source sample (a source derivation edge). The model's output provided a quantified quality gradient (C highest, D moderate, A

and B lowest) and, via explainability techniques, highlighted the conflicting temporal edge as the key factor for auditor review, effectively prioritizing the investigation.

4 Conclusion

This research has presented a novel, machine learning-driven framework for assessing the quality of evidence in environmental audits. By reconceptualizing the audit evidence corpus as a structured, attributed graph and introducing the hybrid HEQ-Net architecture, we have demonstrated that computational methods can achieve high alignment with expert judgment on a complex, qualitative assessment task. The work makes several original contributions. First, it provides a formal graph-based model for audit evidence, a representation that can benefit future research in audit analytics. Second, it introduces a viable machine learning methodology for a domain dominated by heuristic evaluation, showing that relational reasoning is crucial for accurate quality inference. Third, our results reveal that models can learn subtle, latent features of evidence quality that complement traditional audit frameworks, offering the potential for decision support tools that enhance auditor efficiency and consistency.

The implications are significant for the practice of environmental assurance. As sustainability reporting faces increasing scrutiny, the ability to systematically and scalably evaluate the underlying evidence base will be paramount. The techniques described here could be integrated into audit management software to triage evidence, flag potential quality anomalies, and provide explanatory rationales for quality scores. Future work will focus on applying HEQ-Net to real-world audit datasets (subject to confidentiality constraints), extending the model to predict aggregate audit risk scores, and exploring its adaptability to other assurance contexts such as social or safety audits. This study establishes a foundational bridge between advanced machine learning and the critical, yet computationally underexplored, field of environmental audit science.

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