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International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/
Research Paper Open Access

Ethical AI Frameworks For Governance Of Intelligent Systems

E. Angelena Asha Chelliah[1], Ganesh Pathak[2], Shailesh Tripathi[3], Mahendihasan S. Heera[4], Amanveer Singh[5], Vinitha M[6], Bhavadharani S[7]

[1] Assistant Professor, Department of Commerce, Sir Theagaraya College, Chennai, Tamil Nadu, India. Email: aasha_104@rediffmail.com, ORCID: 0000-0002-3552-2947
[2] Associate Professor, Balaji Institute of Modern Management, Sri Balaji University, Pune – 411033, Maharashtra, India. ORCID: 0000-0003-0427-2145
[3] Professor, Balaji Institute of Management and Human Resource Development, Sri Balaji University, Pune, Maharashtra, India. Email: motivationtripathi@gmail.com
[4] Assistant Professor, Faculty of Computer Science and Application, Gokul Global University, Sidhpur, Gujarat, India. Email: mahendihasan.gcca@gokuluniversity.ac.in, ORCID: 0009-0001-9450-2866
[5] Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab 140401, India. Email: amanveer.singh.orp@chitkara.edu.in, ORCID: 0009-0008-9361-4664
[6] Assistant Professor, Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: vinitham@maher.ac.in
[7] Assistant Professor, Department of Commerce, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: bhavadharani@maher.ac.in

Abstract
The rapid adoption of intelligent systems in data-driven domains has amplified concerns regarding transparency, accountability, and governance in artificial intelligence (AI). Existing investigations often address either predictive performance or ethical compliance independently, resulting in limited integration between intelligent decision-making and responsible AI governance. This research proposes a Deep Learning (DL)–based Ethical AI process for governing intelligent systems. that combines advanced DL with structured ethical governance mechanisms. The Environmental, Social, and Governance (ESG) Financial Governance Dataset contains 4000 records and 14 columns describing financial performance indicators, ESG metrics, governance attributes, risk factors, and sustainability-related variables. The proposed method integrates a Sine Cosine Algorithm-fused Efficient Long Short-Term Memory (SCA-ELSTM) model for deep feature learning and ESG risk prediction; SCA used to tunes the model parameters to improve prediction accuracy, convergence speed, and overall learning performance. ELSTM **i**s used for deep feature learning and temporal dependency extraction, an Ethical Governance and Transparency Analytics (EGTA) for ethical risk assessment, governance compliance monitoring, transparency evaluation, and bias analysis; LIME- based local interpretability analysis to balance predictive performance, governance reliability, and sustainability objectives. Experimental results demonstrate substantial improvements over conventional approaches using Python. The proposed model achieves better accuracy (98.28%), precision (97.38%), recall (97.48%), F1-score (97.36%), and reduced error rate of 1.63 while enhancing governance-oriented decision intelligence. The findings validate the effectiveness of integrating ethical governance analytics, explainable AI, and DL optimization for developing trustworthy, transparent, and sustainability-driven intelligent systems.

Keywords: Ethical Artificial Intelligence (AI), AI Governance, Intelligent Systems, Deep Learning, Financial Forecasting, Trustworthy AI

1. Introduction

The increasing use of Artificial Intelligence (AI) technology in the health care industry and various fields has made the requirement of ethical guidelines necessary in order to enable responsible decision-making. Even when AI is being used widely, the task of ensuring that AI technology uses ethics, is transparent and accountable and is responsible becomes difficult [1]. Environmental, Social, and Governance (ESG) assessments have gained prominence as effective tools for assessing sustainability performance of corporations and guiding sustainable investment decisions. The complexities involved in making ESG evaluations are such that understanding assessment results is problematic, thus affecting the interpretability and reliability of sustainability evaluations [2].Various automated decision-making techniques are becoming more widely used in financial institutions to enhance efficiency in the credit scoring process. Current automated decision-making approaches for credit scoring may lack transparency and impartiality, leading to issues of bias and lack of accountability on the part of the stakeholders [3].

Many businesses have come up with the integration of artificial intelligence with sustainable development activities to enhance their environmental, social, and governance impact. It is becoming increasingly challenging to align the organizations' sustainability goals with ethical, environmental, and governance decision-making processes through a AI [4]. A proper evaluation of ESG performance is crucial for both investors and regulators who are interested in improving the sustainability of business activities. It is difficult to forecast ESG ratings due to multiple data sources, changing indicators of sustainability, and complicated connections between ESG criteria [5].

The development of sustainable smart cities is becoming more dependent on intelligent systems to achieve effective use of resources and efficient urban governance policies. It is difficult to make decisions in order to ensure governance while simultaneously meeting various sustainability objectives [6]. As companies embrace AI technologies, they will need appropriate governance processes in place at all stages of the data life cycle for their responsible use. Companies struggle with implementing ethics consistently at all phases, including data collection, processing, implementation, and monitoring, which leads to governance and compliance problems [7].

The increased use of intelligent systems raises questions related to issues of transparency, and Environmental, Social, and Governance (ESG) compliance, where current solutions give more importance to performance rather than ethics and explainability. For tackling such issues, the research proposes the DL-Driven Ethical AI for the Governance of Intelligent Systems involves an SCA-ELSTM for ESG risk prediction and deep feature extraction, as well as an EGTA module for ethical risk analysis, governance compliance checking, transparency analysis, and bias identification.

Research Organization: Introduction to ethical Artificial Intelligence (AI) governance, ESG-driven intelligent systems, and existing research presented in Sections 1 and 2. Section 3 describes the proposed method. Sections 4 present the performance evaluation results. The discussion and conclusion with future research directions is provided in Section 5 and Section 6.

2. Related Work

Current AI governance approaches provide for better explainability and responsible financial intelligence within various intelligent systems. Nonetheless, these still have some constraints in terms of limited validation in different applications, and lack of a standardized evaluation, all these were demonstrated in Table 1.

Table 1: Summary of Existing AI Governance and ESG-Based Approaches

Ref. No.	Objective	Method	Results	Limitations
[8]	Trustworthy AI principles were integrated into lifecycle-based development and operation stages.	Trustworthy AI Maturity Model (TAIMM) to operationalize ethical and legal AI governance.	Evaluated AI governance maturity and regulatory compliance.	Required broader validation across diverse AI applications and organizational settings.
[9]	Verified and audited the fairness of Machine Learning (ML) systems while preserving privacy and ensuring transparency.	Secure Multi-Party Computation (MPC) model is used for distributed computation protocols.	Sensitive data and supported auditing across different ML models and fairness metrics.	Requires additional resources for large-scale deployment and verification.
[10]	Constructed an ESG focused on maintaining low risk and strong compliance.	Long Short-Term Memory (LSTM) neural networks are	Generated portfolios with low ESG risk, low volatility, and returns	Performance depended on prediction accuracy and the historical market.

		used for stock-price prediction.	closely matching the benchmark	
[11]	Improved transparency, auditability, and causal reasoning in ESG while reducing vulnerability to greenwashing.	Variational Graph Neural Networks (VGNNs) are used for counterfactual learning and hybrid deliberation.	Achieved explainable ESG reasoning and improved robustness against misleading ESG claims.	Potential scalability challenges in diverse ESG environments.
[12]	Develop an accurate and interpretable ESG rating prediction model.	Extreme Gradient Boosting is used for predicting ESG ratings	Achieved Accuracy: 91.0%; Precision: 90.7%; F1-score: 90.1%; AUC: 0.977.	Limited generalizability due to potential data bias from ESG rating distributions.
[13]	Improved Annual ESG scores and monthly stock return forecasting	LSTM network used for financial and ESG features.	Improved forecast accuracy and showed meaningful performance advantage over the model.	Used annual ESG data for monthly forecasting, which was limited to temporal relevance.
[14]	Investigated the role of Generative AI (GenAI) in finance and future research directions.	Structural Topic Modeling (STM) for GenAI applications in financial systems.	Identified growing opportunities for decision support and automation.	Lack of standardized evaluation methods.
[15]	Ranked AI-enabled ESG strategies based on decision-making conditions.	Multi-Criteria Decision-Making (MCDM) model to assess seven ESG-driven sustainability strategies.	Sustainable Supply Chain Optimization demonstrating the effectiveness of AI-supported ESG evaluation.	Findings were influenced by expert evaluations, fuzzy logic assumptions, and selected assessment criteria.

In today's intelligent systems and AI governance, there are numerous limitations, including disconnectedness with ethical theories, inability to enforce AI governance, static analysis, and balance between predictive efficiency and sustainable objectives [8–15]. This research aims to solve the above-mentioned issues with a proposed technique using the SCA-ELSTM to achieve flexibility, balance, and reduction in biases.

3. Proposed Methodology

Developed a DL-Based Ethical AI process for the Governance of Intelligent Systems that promotes transparency, governance, and ethical behavior with accuracy and consistency. The suggested approach is demonstrated in Figure 1 below. The ESG Financial Governance data is collected and preprocessed via data normalization and missing values handling, while deep feature learning employing SCA-ELSTM and EGTA to check governance, and decision-making.

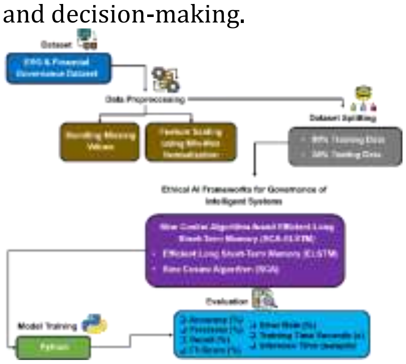


Figure 1: Proposed Ethical AI Governance for SCA-ELSTM Model

3.1 Data Collection

The ESG Financial Governance Dataset is gathered for this research from Kaggle platform. This dataset contains structured financial, ESG, and ethical governance indicators designed to support intelligent system analysis and sustainability-focused decision-making. It includes 4000 rows with 14 columns and multiple numerical and categorical attributes representing corporate performance, sustainability alignment, and governance risk factors. For experimental evaluation, the dataset is divided into an 80:20 ratio, where 80% is for training and 20% for testing. Source: https://www.kaggle.com/datasets/zara2099/esg-financial-governance-dataset/data

3.2 Data preprocessing

Data preprocessing is critical in addressing the issue of data quality and involves the use of techniques such as Missing Value Handling for Data Quality Enhancement, followed by normalization using Min-Max scaling.

- **Missing Value Handling for Data Quality Enhancement:** Missing values from the ESG Financial Governance Dataset are identified during the pre-processing stage and then handled accordingly to conduct valid data analysis. Numerical attributes are imputed by the use of median imputation, whereas categorical attributes are imputed based on the mode attribute. This process reduces data loss and increases data completeness and validity for analysis.
- **Min-Max Normalization for Feature Scaling:** After handling the missing values, the Min-Max technique is used to normalize features that vary in scale into a specific range, usually 0 to 1. It ensures that there are no scale differences between ESG and financial features and avoids bias by those with higher numbers in the training process.

$$\psi_{p,q} = \left[\frac{Z_{p,q}-\min(Z_q)}{\max(Z_q)-\min(Z_q)} \times M\right] \quad (1)$$

Equation (1) shows that $\psi_{p,q}$ denotes the normalized and discretized value of the q^{th} attribute for the p^{th} sample. $Z_{p,}$ q represents the original value of the q^{th} attribute for the p^{th} sample. min $(Z_q)$and max $(Z_q)$are the minimum and maximum values of the q^{th} attribute across all samples. Mis the scaling factor that determines the number of discrete levels. However, Min-Max normalization standardizes all features of ESG and finance to a consistent scale, which yields uniformly scaled feature values and stability throughout the entire convergence process.

3.3 Ethical Governance and Transparency Analytics (EGTA) for Responsible AI Decision-Making

The EGTA module aims to analyze the ethical and governance perspectives associated with the ESG risk prediction. In addition to attaining high predictive performance, the proposed approach places emphasis on the ethical use of AI and integrates ethical risk assessment, governance compliance analysis, transparency assessment, and decision-making reliability analysis.

ESG-Based Ethical Risk Evaluation and Governance Integrity Assessment: The Ethical Risk Assessment Module quantifies the ethical standing of an organization by integrating information from the Ethical Risk Index, Governance Score, and Compliance Score attributes. A weighted aggregation mechanism is employed to calculate the Ethical Risk Score (ERS), which serves as a comprehensive measure of ethical performance. Organizations with lower ethical risk, stronger governance structures, and higher compliance levels obtain higher ERS values.

Explainable AI-Based Transparency and Explainability Analysis: Interpretability and Explainability Module uses the Local Interpretable Model-Agnostic Explanations (LIME) method to gain explanations about how decisions are made by the SCA-ELSTM. LIME creates local surrogate models for each prediction, which allows identifying the key financial, governance, sustainability, and ethical risk factors behind the particular result in classifying the company into one of the three risk categories: Low Risk, Medium Risk, and High Risk.

Bias Detection and Decision Reliability Evaluation: The Bias and Decision Reliability is concerned with checking for the consistency and robustness of ESG classification results. This module evaluates the decisions' reliability by using the Decision Reliability Score (DRS). This score is calculated using the difference between predicted and actual values of the ESG risk class.

3.4 SCA-ELSTM: ESG Risk Prediction and Optimization for Reliable Decision-Making

The SCA-ELSTM model enhances ESG risk prediction through optimized DL while maintaining accurate and reliable decision-making performance. In particular, the SCA fine-tunes parameters and representation of features to ensure better convergence and prediction performance, while the ELSTM model classifies risks in an effective manner using learned interdependencies among financial, governance, and ethical risk indicators.

3.4.1 ELSTM for Ethical AI Governance and ESG Performance Prediction

Long Short-Term Memory (LSTM) is ideal for sequential pattern extraction and analysis as it can handle complex long dependencies. However, conventional LSTM models was struggled with slow convergence, inability to capture highly complex dependency patterns, sensitivity to hyperparameters, and working with heterogeneous ESG governance data. Thus, the ELSTM model can increase accuracy and provide reliable prediction results in classifying and managing ESG risks.

As input data, ELSTM takes financial indicators, ESG scores, governance metrics, ethical risk elements, compliance data, sustainability criteria, and sequential data. The goal of applying the ELSTM model is to recognize complex temporal dependencies and changing patterns in finance, governance, and sustainability data. Improved memory and forgetting capabilities allow ELSTM to preserve important data and filter irrelevant data, which helps in predicting ESG performance, ethical compliance, and intelligent results.

$$M_t = g_t M_{t-1} + (1 - g_t)\widetilde{M}_t \tag{2}$$

Equation (2) shows M_t t represents the new memory state at time t, holds all necessary data for making predictions in the future. The term g_t represents the forget gate value. The variable M_{t-1} refers to the memory state at time. The term $(1-g_t)$ decides the amount of new data that is to be added to the memory state. The variable $\widetilde{M}_t$ refers to the candidate memory state.

$$g_t = \sigma\left(W_g \begin{bmatrix} M_{t-1} \\ s_{t-1} \\ u_t \end{bmatrix} + b_g\right) \tag{3}$$

In equation (3), W_g represents the forget gate vector of step t, that controls how much historical data needs to be remembered for future predictive work. The function σ denotes the sigmoid activation function that maps the gate values between 0 and 1. The term W_g is the learnable weight matrix of the forget gate. The variable M_{t-1} represents the previous memory state of financial performance, ESG indicators, governance attributes, and ethical risk information. The term s_{t-1} refers to the previous hidden state. The variable u_t represents the current input vector consisting of financial, sustainability, governance, and ethical features at time step t. The parameter b_g is the bias vector that assists in adjusting the forget gate computation. However, the ELSTM predicts performance of ESG, effectiveness of governance, ethical compliance scores, and sustainable results, aiding accurate and reliable decision-making. The ELSTM architecture is shown in Figure 2. It depicts the flow of ESG input features through memory and gate operations to generate the ESG risk classification output

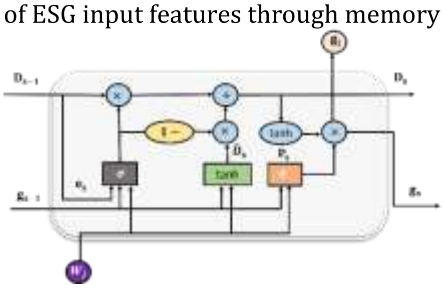


Figure 2: Internal gating mechanism of the ELSTM network

3.4.2 SCA for Ethical AI Governance and Intelligent System Performance

The SCA adaptively tunes the SCA-ELSTM hyperparameters and the ethical governance goals through the optimization of predictive accuracy, fairness, transparency, regulatory compliance, and sustainability performance. It includes financial indicators, ESG data, governance parameters, sustainability constraints, and potential solutions produced by the intelligent system. The SCA employs predictions, ethical considerations, compliance with regulations, and sustainability issues are taken into consideration. It uses the combination of global search by means of sine and cosine approaches and a local search to achieve the desired results and minimize bias.

$$y_{j,k}^{u+1} = \begin{cases} y_{j,k}^{u} + s_1 \sin(r_2) \mid r_3 q_{best,k}^{u} - y_{j,k}^{u} \mid, & s_4 < 0.5 \\ y_{j,k}^{u} + s_1 \cos(r_2) \mid r_3 q_{best,k}^{u} - y_{j,k}^{u} \mid, & s_4 \geq 0.5 \end{cases} \tag{4}$$

In equation (4), $y_{j,k}^{u}$ denotes the current value of the k^{th} decision variable of the j^{th} candidate solution at iteration u, while $y_{j,k}^{u+1}$ represents its updated value in the next iteration. The variable $q_{best,k}^{u}$ indicates the k^{th}

component of the best solution considering governance and performance objectives. The parameter s_1 controls the search step size and balances the exploration and exploitation process. The random variable r_2 determines the movement direction through sine or cosine functions. The parameter r_3 is a scaling factor that adjusts the influence of the best solution on the current candidate solution. The variable s_4 is a random decision parameter, where values greater than 0.5 activate the sine update mechanism and values less than or equal to 0.5 activate the cosine update mechanism. The indices j and k represent the candidate solution, respectively, while u denotes the current iteration number.

$$s_1 = b - u\left(\frac{b}{U}\right) \tag{5}$$

Where equation (5), s_1 is the adaptive control parameter that balances global exploration and local exploitation, b is a constant (typically set to 2), udenotes the iteration number, and U denotes the iterations of maximum number. However, an algorithm generates an optimized parameter that leads to intelligent systems that are ethically governed and transparent, which results in increased efficiency.

The SCA-ELSTM is designed for ESG risk prediction and intelligent governance assessment in sustainability-driven organizations. The system effectively identifies ESG risk levels using financial, environmental, social, and governance indicators. The integrated model improves prediction accuracy while minimizing classification errors during decision-making processes.

4. Results

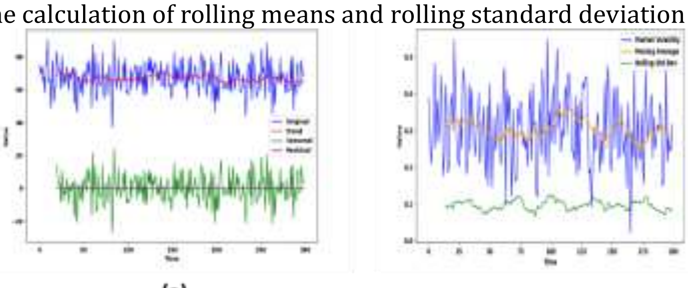
The Ethical AI for Governance of Intelligent Systems based on ESG was efficiently designed with the help of the SCA-ELSTM. Experiments were carried out on Intel Core i7-14700K CPU, 32 GB DDR5 RAM, NVIDIA RTX 4070 GPU and 12 GB VRAM, along with Python 3.11, TensorFlow 2.16, Keras 3.0, NumPy, Pandas, Scikit-learn. This section offers the findings Experimental Analysis, Per-Class Performance Analysis, Explainability Analysis, Descriptive Statistics, Comparative Performance and Computational Analysis, Governance, Sustainability, and Decision Optimization Analysis used for effective governance compliance, sustainability-oriented decision-making, and optimized intelligent system performance.

4.1 Evaluation Metrics

Accuracy (%): The metric measures the overall rate of classification accuracy, Precision (%): It shows the percentage of correct classification of positive ESG risk instances out of all predictions, Recall (%):Measures the ability of the model to identify actual positive ESG risk instances, F1-Score (%):denotes the mean of precision and recall, providing a balanced performance measure, Error Rate (%): Quantifies the percentage of incorrectly classified ESG risk instances. Lower values indicate better performance, Training Time (Seconds): denotes the time required to train the proposed method, Inference Time (ms): Measures the average time required to generate a prediction for a single sample.

4.2 Experimental analysis

The dynamics for the ESG Index and Financial Performance are determined by decomposing the ESG index into trends and residuals for sustainability tendencies over time, in addition to evaluating market volatility through the calculation of rolling means and rolling standard deviation over time, as shown in Figure 3.



(a) (b)

Figure 3: ESG Index Time-Series Analysis of (a) Illustrates that to temporal variation in ESG scores over time, and fluctuations in environmental, social, and governance performance and (b) Depicts the variation in financial stability over time, highlighting periods of high and low uncertainty to understand dynamic risk behavior and performance stability.

The ESG index ranges from approximately 35 to 85 units, with a stable trend around 67 units, indicating consistent long-term ESG performance is shown in Figure3(a). Residual fluctuations between −25 and +20 units reflect short-term variations around this stable trend, and Figure 3(b) represents market volatility ranges from 0.05 to 0.60, with a stable rolling average of 0.25–0.35 and low standard deviation (0.08–0.12), indicating moderate and controlled financial variability suitable for ESG-based analysis.

➤ **Per-Class Performance Analysis:** Class-based analysis reveals the effectiveness of the SCA-ELSTM approach in categorizing different ESG risks through the accurate predictive performance obtained in the High Risk, Medium Risk, and Low Risk classes. The findings show that the suggested model is capable of maintaining an effective balance between precision and recall in assessing ESG risks, as shown in Table 2.

Table 2: Performance assessment of per-class classification

ESG Risk Class	Precision (%)	Recall (%)	F1-Score (%)
High Risk	96.02	87.11	91.35
Low Risk	93.94	67.39	78.48
Medium Risk	93.23	98.39	95.74

The SCA-ELSTM achieved 96.02% precision, 87.11% recall, and 91.35% F1-score for the high-risk class. For the low-risk class, the model attained 93.94% precision, 67.39% recall, and 78.48% F1-score, indicating high prediction accuracy with relatively lower detection coverage. The Medium Risk class achieved 93.23% precision, 98.39% recall, and 95.74% F1-score, reflecting excellent classification capability and balanced predictive performance

➤ **Explainability Analysis Using LIME:** The significance of the various inputs is evaluated by employing LIME-based Explainability to ascertain the important drivers of ESG risk prediction. This has been accomplished through the identification of the impact of governance, compliance, ethical risk, transparency, sustainability, and financials on the prediction process, hence enhancing the reliability of decisions based on governance, as shown in Figure 4.

Figure 4: Instance-Level Feature Contribution Analysis Using LIME

4.3 Descriptive Statistics of ESG Financial Governance Dataset

The ESG Financial Governance Dataset consists of various indicators related to finance, governance, transparency, sustainability, and ethics that collectively facilitate ESG risk categorization. All input attributes are statistically profiled in Table 3. The Mean represents the average value of a feature, Standard Deviation indicates the variability or dispersion of the data, Minimum denotes the smallest observed value, and Maximum represents the largest observed value. The obtained results demonstrate high variation within the dataset that allows the proposed method to identify various governance and sustainability patterns.

Table 3: Descriptive Statistics of ESG Financial Governance Dataset

Feature	Mean	Standard Deviation	Minimum	Maximum
Revenue	502.32	119.66	111.05	971.15
Profit Margin	14.84	6.10	-7.13	36.17
Debt Ratio	0.45	0.20	-0.33	1.13
Cash Flow	201.93	80.60	-90.82	558.33
Market Volatility	0.30	0.10	-0.09	0.69
Environment Score	64.71	14.80	10.17	100.00
Social Score	70.03	11.77	28.06	100.00
Governance Score	67.73	13.91	18.54	100.00
Ethical Risk Index	12.91	7.32	0.00	41.65

Bias Indicator	0.20	0.10	0.00	0.53
Transparency Score	0.70	0.15	0.06	1.00
Compliance Score	67.49	7.87	37.04	93.80
Feature Importance Entropy	0.50	0.20	0.00	1.00

4.4 Comparative Performance and Computational Analysis

The comparative analysis of the SCA-ELSTM is performed by comparing its performance with existing methods, including the Cognitive AI-Governance-Empowered FinTech Ecosystem (CAI-GFE) [16] approach, wherein it employs a Temporal Fusion Transformer (TFT) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II). All methods were retrained and assessed by ESG Financial Governance Dataset with the same data partition and process. The comparative analysis results in terms of ESG risk prediction and governance assessment are shown in Table 4. The proposed method shows better performance compared with others, with a 98.28% accuracy, 97.38% precision, 97.48% recall, and 97.36% F1-score, indicating highly effective ESG risk classification. In addition, the model recorded a low 1.63% error rate, with a training time of 4.78 seconds and an inference time of 0.0087 ms, demonstrating excellent computational efficiency.

Table 4: Performance Assessment of Comparative and Computational Analysis

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Error Rate (%)**	**Training Time (s)**	**Inference Time (ms)**
CAI-GFE	93.88	93.95	93.88	93.69	6.13	6.55	0.0799
SCA-ELSTM [Proposed]	98.28	97.38	97.48	97.36	1.63	4.78	0.0272

- **Governance, Sustainability, and Decision Optimization Analysis**

The comparison between the performance of ESG classification and the current CAI-GFE model is shown. The improvement signifies the benefits obtained from combining deep sequential learning and evolutionary optimization. Furthermore, the reduction in error rate highlights that better generalization capability across heterogeneous financial and ESG indicators is shown in Table 5.

Table 5: Comparative Governance & ESG Performance Analysis

Metric	**CAI-GFE**	**SCA-ELSTM [Proposed]**
ESG Compliance Accuracy (%)	88.7	94.1
Governance Compliance Score	0.84	0.92
Ethical Risk Assessment Score	0.78	0.88
Transparency Score	0.79	0.90
Decision Reliability Score	0.82	0.93
Sustainability Alignment (%)	86.5	94.8
Profitability Improvement (%)	4.1	10.6

5. Discussion

The developed integrated ESG risk prediction and ethics governance for AI is effective for making transparent, reliable, and governance-based decisions. Traditional approaches that involved the use of CAI-GFE [16] faced various difficulties in relation to predictive capabilities, transparency, and ethics analytics integration. In addition, the existing models were characterized by the lack of adequate tools for ESG compliance assessment, ethics risk analysis, and decision reliability verification. Meanwhile, the SCA-ELSTM improves the mentioned aspects significantly while providing reliable decision results. Thus, the discussed model was regarded as an efficient approach for intelligent system governance and ESG-related decision-making using AI.

6. Conclusion

The ethical AI governance SCA-ELSTM was effectively developed to ensure trustworthy, transparent, and robust decision-making. It utilizes the ESG Financial Governance Dataset, with preprocessing including normalization and missing-value handling, while SCA-based optimization with ELSTM method enhance predictive performance. The proposed model demonstrates strong results in accuracy (98.28%), precision (97.38%), F1-

score (97.36%), Recall (97.48%), Error Rate (1.63%), Training time (4.78s), and inference time (0.0272ms). The model is limited in data size and dataset distribution variability, while future work may focus on improving the data size, real-time ESG monitoring, cross-domain generalization, and scalable ethical AI deployment in dynamic financial environments.

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