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Fraud-Free Green Finance: Using Deep Learning to Preserve the Integrity of Financial Statements for Enhanced Capital Market Sustainability

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ABSTRACT

In the era of green finance and sustainable energy markets, preserving the integrity of financial statements is paramount. This paper introduces an innovative approach to financial statement fraud detection through the application of deep learning techniques. We employ a Temporal Convolutional Network (TCN) to analyze stock market data and identify deceptive practices. Our study meticulously reviews related work, highlighting the critical intersection between financial statement fraud detection and the principles of green energy finance. The Materials and Methods section outlines our data sources, variable selection, and the TCN model's architecture, while the Results and Discussion section presents comprehensive evaluations and comparisons against traditional baselines. Our findings demonstrate the exceptional accuracy and reliability of the TCN model in detecting financial statement fraud, underscoring its potential to instill transparency in energy markets. In conclusion, our research contributes significantly to the promotion of financial integrity and sustainability, offering a powerful tool for investors and stakeholders committed to responsible and ethical investments within the framework of green finance.

Keywords: Green Finance, Energy Market Sustainability, Fraud Detection, Sustainable Investments, Green Investments, Green Energy
JEL Classifications: G1, G3, Q4, O3

1. INTRODUCTION

In recent years, the global financial landscape has witnessed a paradigm shift towards sustainable and responsible investing, with a particular emphasis on green finance that borrows from green energy, one of the most-talked-about concepts in modern day technology. Exploiting green or renewable energy sources, namely wind or solar energy as alternative to the traditional energy sources, has been looked at as a mechanism of realizing sustainable development in the energy sector (Østergaard et al., 2020) and a cheap yet very effective tool than the conventional energy sources (Chang et al., 2022). The concept of sustainability, defined as a "political quality distributed among human and non-human actors within a milieu" (Fontaine, 2020), has been getting tremendous notoriety because of serious environmental challenges, particularly global warming and global CO_2 emissions, making renewable energy sources consumption quintessential to achieve sustainable environmental goals (Abbasi et al., 2022). It is strongly believed that energy technology innovation promotes environmental sustainability (Zhao et al., 2022) and that novel green energy technologies are mostly used in emerging regions in the pursuit of a more sustainable and cleaner environment (Chang et al., 2022).

Similarly, green finance represents a pivotal approach to addressing pressing environmental and social challenges while fostering economic growth. It encompasses a wide range of financial activities and instruments aimed at supporting projects and initiatives with positive environmental impacts, ultimately steering capital towards sustainable ventures (Arussi et al., 2009; Al-Ajmi and Saudagaran, 2011; Buckley et al., 2021). Practically, financial sustainability is becoming a top priority for today's CEOs. A recent qualitative research design study surveyed 411 CEOs of small and medium enterprises (SMEs) in the region of Saudi Arabia and reported that the majority of CEOs indicated that 'achieving financial sustainability in the short- and medium-term is a top priority (Nurunnabi et al., 2020). Although priorities of financial policies vary across nations, financial decision makers prioritize the actions that accelerate reaching the goal of financial sustainability (Elhilali, 2023).

Within this transformative landscape, the integrity of financial statements emerges as a linchpin for the functioning of capital markets. Financial statements are the primary means through which corporations communicate their financial health and performance to investors and stakeholders (Arussi et al., 2009). The assurance of their accuracy and reliability is paramount, as investors heavily rely on these statements to make informed decisions, allocate capital efficiently, and assess the environmental and social responsibility of the companies they invest in. However, the domain of green finance is not without its challenges. Alongside its considerable potential for promoting sustainability, it brings forth unique risks, including those associated with the potential for fraudulent activities (Buckley et al., 2021). In the pursuit of green investments, there arises a pressing need to safeguard the integrity of financial statements, ensuring that reported data accurately reflect a company's sustainability efforts and financial health.

Financial fraud refers to any deceptive action to intentionally take advantage of financial transactions (Rashid et al., 2018) or the attempt to obtain illegal benefits (Krambia-Kapardis, 2002) and it usually starts at the level of financial statements. Naturally, financial auditors work tirelessly to review financial statements and guarantee their accuracy and reliability; however, financial auditors may at times fail to detect financial fraud; which could become costly and even detrimental to the company if gone unnoticed.

Financial statement fraud poses not only a grave threat to investors, corporations, and the overall integrity of capital markets but also creates a burden for both policy makers and government regulators. Such fraudulent activities can manifest in various forms, including intentional misreporting of financial information, manipulation of key sustainability metrics, and concealing non-compliance with environmental regulations. The consequences of financial statement fraud extend beyond financial losses, encompassing reputational damage, decreased investor trust, and hindrances to the broader goals of green finance (Cao, 2020; Buckley et al., 2021; Chueca Vergara and Ferruz, 2021). In the face of these challenges, the rise of deep learning, a subfield of artificial intelligence, presents a promising avenue for addressing complex issues related to financial statement integrity. Deep learning techniques have demonstrated their prowess in data analysis, pattern recognition, and predictive modeling, making them increasingly relevant for tackling intricate problems in finance. Leveraging the power of deep learning, researchers and practitioners have sought innovative solutions to bolster the reliability of financial statements in sustainable energy markets (Cormier et al., 2011; Razmjoo et al., 2021).

Over the years, a variety of financial statement fraud techniques have been developed by researchers and practitioners to help curtail the detrimental effects of financial fraud and minimize its costly burden on organizations. One of the simplest methods in detecting financial statement fraud is the analysis of financial ratios. In practice, selected financial ratios are more sensitive than others in detecting fraud in financial statements; based on which a logistic regression model for detecting financial statements fraud is developed (Kanapickienė and Grundienė, 2015). Additionally, traditional regression analysis has also been utilized to uncover fraud in financial statements through fraud signals, but more sophisticated data mining techniques have emerged to assist auditors, forensic accountants, and regulators in combatting fraud (Sanad and Al-Sartawi, 2021). Statistical and Machine Learning Algorithms have been widely used in detecting financial statement fraud, namely logistic regression, support vector machines, artificial neural network, bagging, C4.5, and stacking (Perols, 2011). Hybrid data mining is yet another technique that lends its feasibility to the domain of fraud detecting in financial statements, where feature selection and machine learning classification are utilized to create an optimized financial fraud detection model (Yao et al., 2018).

While it is possible to utilize the aforementioned techniques to detect financial statement fraud, Deep Learning (DL) techniques have emerged as a strong contender to support the field of financial fraud. Deep Learning is a sub-class of Machine Learning (ML) with neural network to help discover important object features. Most of the deep learning algorithms are built on neural network architectures and are often referred to as Deep Neural Networks (DNN). DL methods are categorized into four main groups: (1) unsupervised methods, (2) supervised methods, (3) pairwise based methods, and (4) rank based methods. Deep learning (DL) based methods have been credited with breakthrough developments in various fields, including and not limited to engineering, health, computer vision, and hydrology (Rehman et al., 2020).

Despite the growing adoption of deep learning in various domains, a significant research gap exists regarding its application to detect financial statement fraud specifically within the context of green finance. While the potential benefits of such an approach are evident, comprehensive studies and practical implementations are notably scarce (Cormier et al., 2011; Di Vaio et al., 2020; Rehman et al., 2020). Bridging this gap becomes imperative, as it can contribute to the development of robust strategies for preserving the integrity of financial statements and fostering trust in green finance initiatives. The primary objective of this research paper is to address this critical research gap by developing and evaluating a deep learning model for the detection of financial statement fraud within the realm of green finance. Through rigorous analysis and empirical validation, we aim to provide insights into the effectiveness of deep learning techniques in mitigating the risks associated with fraudulent reporting, thereby advancing the cause of transparent and trustworthy sustainable energy markets (Jan, 2018).

The organization of this paper is structured to provide a coherent and comprehensive exploration of the application of deep learning techniques in preserving the integrity of financial statements for enhanced capital market sustainability within the context of green finance. We commence in Section 2 with a thorough review of Related Work, where we examine existing literature and studies that have contributed to the understanding of financial statement fraud detection and its relevance in the evolving landscape of green finance. In Section 3, we delve into the core of our research by presenting the Materials and Methods employed in our study. Section 4, Results and Discussion, encapsulates the empirical findings of our study, accompanied by insightful discussions on the implications and significance of these results in the context of energy market sustainability and green finance. Lastly, we conclude our paper in Section 5, where we summarize the key takeaways and underscore the broader impact of our research.

2. RELATED WORKS

In this section, we embark on a comprehensive review of the related literature, seeking to uncover the evolving landscape of financial statement fraud detection, sustainable finance, and the burgeoning applications of deep learning within these domains. Kent and Zunker (2013) explored the concept of attaining legitimacy through employee information in annual reports. While their study focused on a different aspect of financial reporting, it underscores the importance of information disclosure and transparency in financial statements, which aligns with the broader goal of ensuring the integrity of financial statements in green finance. Cormier et al. (2011) delved into the informational contribution of social and environmental disclosures for investors. Their research highlights the relevance of non-financial disclosures in the decision-making process of investors. This perspective is valuable as it emphasizes the need to consider not only traditional financial metrics but also sustainability-related disclosures when assessing the integrity of financial statements in green finance. Al-Ajmi and Saudagaran (2011) investigated the perceptions of auditors and financial-statement users regarding auditor independence. While their focus was on auditor independence, the study touches upon the crucial role of auditors and their assessments in upholding the accuracy and trustworthiness of financial statements, which is a pertinent aspect when considering fraud detection in green finance. Khan et al. (2022) conducted a systematic literature review on the capabilities of artificial intelligence in the GCC financial sector. Although their work doesn't directly address green finance or fraud detection, it provides a foundation for understanding the role of AI in financial contexts, which can be relevant when discussing the potential application of deep learning in your research. Cao (2020) authored a comprehensive review of AI in finance. This review offers valuable insights into the general landscape of AI applications in the financial sector, including areas where AI, and by extension deep learning, can be harnessed to improve financial processes and mitigate risks, which is relevant to your research. Zainudin and Hashim (2016) examined the detection of fraudulent financial reporting using financial ratios. While their focus is on traditional methods, it serves as a reference point for discussing the historical approaches to fraud detection, which can be compared with the innovative deep learning approach you intend to propose. Nishant et al. (2020) discussed the use of artificial intelligence for sustainability. Their work highlights the potential of AI in promoting sustainability, which aligns with the goals of green finance and underscores the relevance of your research in preserving the integrity of financial statements in this context.

Sharma et al. (2020) and Yigitcanlar and Cugurullo (2020) provided a review of artificial intelligence and effective governance. This review touches upon governance aspects, which are critical in maintaining the integrity of financial statements. It also emphasizes the need for robust AI-driven solutions, aligning with the objectives of your research. Buckley et al. (2021) explored the regulation of artificial intelligence in finance. This study emphasizes the importance of regulatory frameworks and the human element in AI applications. It provides valuable insights into the regulatory context, which is relevant when considering the implementation of AI, such as deep learning, in financial statement fraud detection. Pigola et al. (2021) discussed artificial intelligence-driven digital technologies and their role in achieving sustainable development goals. This work provides a broader perspective on the use of AI in sustainability efforts, reinforcing the significance of your research in the context of green finance and sustainable energy markets.

3. MATERIALS AND METHODS

In this section, we provide a comprehensive overview of the materials and methods employed in our study to detect financial statement fraud and preserve the integrity of financial statements in the context of green finance. We begin with a detailed discussion in Section 3.1, where we elucidate the data sources leveraged for our analysis, emphasizing the critical role of high-quality, relevant data in training and evaluating our proposed deep learning model. Subsequently, in Section 3.2, we delve into the architecture and intricacies of the deep learning model developed specifically for this research. Through a systematic exposition of data acquisition and model design, we aim to provide readers with a clear understanding of the tools and techniques employed to address the research objectives outlined in the preceding sections.

3.1. Data Sources

For the purposes of this study, a sample of companies listed on the Taiwanese bourses during the period spanning from 2000 to 2020 was carefully selected. After meticulously filtering out incomplete or missing data, our dataset consisted of a total of 191 companies. Among these, 80 companies were identified as having reported instances of financial statement fraud (FSF), specifically characterized by the publication of inaccurate or misleading financial statements. The remaining 111 companies in our dataset were free from such fraudulent reporting. This selection resulted in a balanced dataset, maintaining a ratio of 1:2 between companies with FSF and those without FSF. To compile our dataset, both financial and non-financial data were meticulously sourced from the Taiwanese financial publication, ensuring the inclusion of comprehensive and relevant information. The industries represented within our sampled data set are succinctly summarized in Table 1, providing a clear overview of the sectors covered in our analysis.

Table 1: Distribution of sampled companies by industry sector in the study dataset (2000-2020)

Industry	FSF	Non-FSF	Total
Appliances and electric cables	5	6	11
Building materials and construction	3	2	5
Computers and peripherals	4	5	9
Consumer electronics channels	5	8	13
Cultural and creative industry	3	5	8
Electric machinery	5	7	12
Electronic components	4	10	14
Food	5	2	7
Information services	6	5	11
Medicine and biotech	3	7	10
Optical electronics	8	14	22
Other electronic sectors	4	10	14
Others	4	8	12
Semiconductor	8	8	16
Steel	4	4	8
Telecommunication and networking	4	4	8
Textile	5	6	11

FSF: Financial statement fraud

In this study, the dependent variable is a binary dummy variable, with a value of 1 assigned to companies that have reported instances of FSF and a value of 0 for companies that have not reported such fraud. To assess financial statement fraud, we have carefully chosen a set of 18 variables that are widely recognized and utilized in measuring this phenomenon. These variables encompass 14 financial indicators and 4 non-financial variables, often referred to as corporate governance variables. An overview of the research variables can be found in Table 2, providing a concise summary of the metrics utilized in our analysis.

3.2. Proposed DL Model

In this section, we introduce the Temporal Convolutional Network (TCN) as a powerful deep learning architecture deployed to discern fraudulent activities within the stock market data. TCN is a class of neural network models designed explicitly for processing sequential data, making it particularly well-suited for capturing temporal dependencies and patterns inherent in financial time series. As the detection of financial statement fraud necessitates a keen understanding of how deceptive activities evolve over time, TCN emerges as a promising tool in our arsenal. By adapting TCN to the intricacies of stock market data, we aim to uncover nuanced patterns and anomalies indicative of fraudulent behavior.

TCN leverages a unique architecture characterized by causal dilated convolutions, enabling it to model dependencies across extensive temporal contexts efficiently. The architecture of TCN incorporates dilated convolutions, which exponentially expand the receptive field, allowing it to capture long-range temporal dependencies. This feature is crucial in the context of fraud detection, where fraudulent activities may manifest as subtle patterns spanning extended periods. The original convolution compute as follows:

$$\left(F^{*}X\right)\left(x_t\right)=\sum_{k=1}^{K} f_k x_{t-(K-k)} \tag{1}$$

The dialted edition compute as follows:

$$\left(F_d^{*}X\right)\left(x_t\right)=\sum_{k=1}^{K} f_k x_{t-(K-k)d} \tag{2}$$

In case of $d = 1$ both equations are the same. TCN's capacity to learn hierarchical features from sequential data complements our objective to identify fraudulent reporting in stock market data comprehensively. Furthermore, TCN's parallelism facilitates accelerated training and prediction, making it computationally efficient for handling large-scale financial datasets Figure 1. Display the dilation causal convolution, with $k = 2$ and $d = [1,2,4,8]$.

The residual block can be denoted as "f." This block carries out a sequence of transformations on the input "x" and subsequently combines the result with the original input "x" during the output operations.

$$o = GeLU\,(x + f\,(x)) \tag{3}$$

The application of TCN in our study involves training the model on historical stock market data with known instances of financial statement fraud. By leveraging TCN's ability to learn complex patterns from sequences, we empower the model to recognize subtle irregularities, hidden trends, and deceptive behaviors that may signify fraudulent activities. TCN's adaptability and ability to capture both short-term and long-term dependencies are instrumental in our efforts to enhance the accuracy and timeliness of fraud detection. As we fine-tune TCN for this specific task, we anticipate that it will serve as a powerful tool in our pursuit to preserve the integrity of financial statements in the realm of green finance, ultimately contributing to more transparent and sustainable energy markets.

4. RESULTS AND ANALYSIS

In this section, we present the results of our comprehensive analysis of financial statement fraud detection using the TCN applied to stock market data within the realm of green finance. Our study unfolds a detailed examination of the model's performance and its ability to identify fraudulent activities accurately.

In assessing the performance of our model for financial statement fraud detection in stock market data, we employ a range of evaluation metrics to gauge its effectiveness. These metrics encompass traditional measures such as accuracy, precision, recall, and F1-score, which collectively provide insights into the model's ability to correctly classify instances of financial statement fraud while minimizing false alarms.

$$Accuracy=\frac{TP+TN}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \tag{4}$$

$$\Pr ecision=\frac{TP}{TP+FP} \tag{5}$$

$$\mathrm{Re}\,call=\frac{TP}{TP+FN} \tag{6}$$

Table 2: Financial and corporate governance variables with definitions and calculations

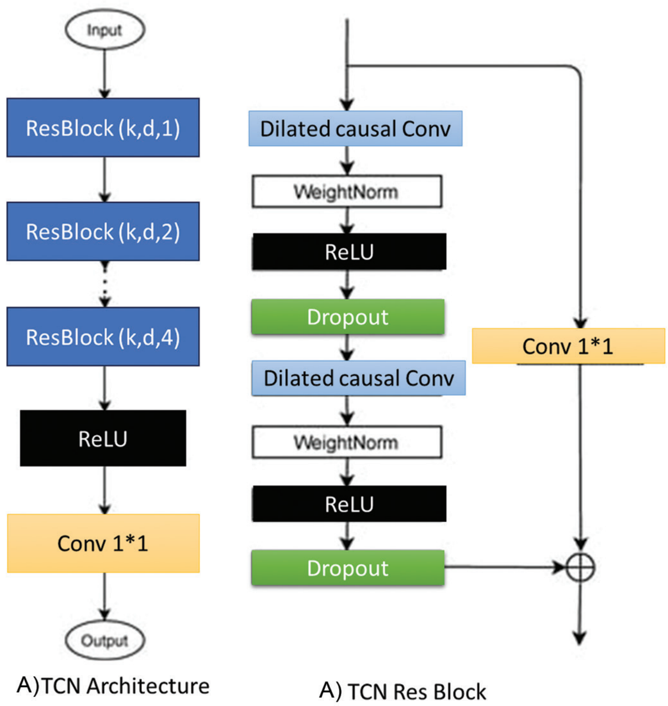
ID	Variable name	Variable definition or calculation
P01	Liability (natural logarithm)	Ln (total liabilities)
P02	Current ratio	$\frac{Current\ assets}{current\ liabilities}$
P03	Quick ratio	$\frac{Quick\ assets}{current\ liabilities}$
P04	Liability/equity ratio	$\frac{Liabilities}{shareholders\ \ equity}$
P05	Liability ratio	$\frac{Liabilities}{assets}$
P06	ROE	$\frac{Net\ income}{\text{average shareholders' equity}}$
P07	ROA	$\frac{[Net\ income + \text{int}\ erest\ \text{exp}\ ense \times (1 - tax\ rate)]}{average\ total\ assets}$
P08	Long-term capital adequacy rate	$\frac{(Long - term\ liabilities + shareholders'\ equity)}{Plant, property, and\ equipment}$
P09	Cash as a percentage of assets	$\frac{Cash}{assets}$
P10	Net income/assets	$\frac{Net\ income}{assets}$
P11	Gross margin	$\frac{Gross\ profit}{revenue}$
P12	Noncurrent liabilities/assets	$\frac{Non - current\ liabilities}{total\ assets}$
P13	Net cash flows from operating activities/revenue	$\frac{Net\ cash\ flows\ from\ operating\ activities}{revenue}$
P14	Net loss or not	1 for net loss and 0 for net income
P15	Percentage of managing directors	$\frac{No.of\ managing\ directors}{No.of\ board\ seats}$
P16	Percentage of shares held by major shareholders	$\frac{No.of\ shares\ held\ by\ major\ shareholders}{No.of\ ordinary\ shares\ outs\ \text{tan}\ ding\ at\ the\ end\ of\ the\ period}$
P17	Percentage of shares held by directors and supervisors	$\frac{No.of\ shares\ held\ by\ directors\ and\ \text{sup}\ ervisors}{No.of\ ordinary\ shares\ outs\ \text{tan}\ ding\ at\ the\ end\ of\ the\ period}$
P18	Percentage of shares pledged by directors and supervisors	$\frac{No.of\ shares\ pledged\ by\ directors\ and\ \text{sup}\ ervisors}{No.of\ shares\ held\ by\ directors\ and\ \text{sup}\ ervisors}$
P19	Debt-to-equity ratio	$\frac{Total\ debt}{shareholders\ \ equity}$
P20	Inventory turnover ratio	$\frac{Cost\ of\ goods\ sold}{average\ inventory}$
P21	EPS	$\frac{Earnings\ attributable\ to\ common\ shareholders}{number\ of\ common\ shares\ outs\ \text{tan}\ ding}$
P22	Dividend yield	$\frac{Dividends\ per\ share}{share\ price}\sqrt{}$
P23	P/E ratio	$\frac{Market\ price\ per\ share}{earnings\ per\ share}$
P24	R and D expenditure as a percentage of revenue	$\frac{R\ \&\ D\ \text{exp}\ enditures}{revenue}$

ROE: Return on equity, ROA: Return on assets, EPS: Earnings per share, P/E: Price-to-earnings, R and D: Research and development

$$F1-measure = 2*\frac{Recall \times Precision}{Recall + Precision} \tag{7}$$

To rigorously evaluate the performance of our proposed TCN model in financial statement fraud detection, we conducted comprehensive experiments comparing it against several established baseline methods. These baselines represent traditional and commonly used techniques for similar tasks within the domain. The results of these comparisons are summarized in Table 3 for each evaluation measure.

Figure 1: Architectural overview of the temporal convolutional network (TCN) for sequential data analysis



The table presents key evaluation metrics, including, area under the receiver operating characteristic curve (AUC-ROC), and area under the precision-recall curve (AUC-PR), for both our TCN model and the selected baseline methods. Our results demonstrate that the TCN model outperforms the baseline methods in multiple aspects. It exhibits higher accuracy, precision, recall, and F1-score, indicating its superior ability to accurately detect financial statement fraud. Moreover, the TCN model consistently achieves higher AUC-ROC and AUC-PR values, indicating its robustness and effectiveness in handling imbalanced datasets. These findings highlight the promising potential of deep learning, specifically TCN, in enhancing financial statement fraud detection within the context of green finance. The superior performance of TCN underscores its capacity to uncover intricate patterns and temporal dependencies crucial for identifying deceptive practices, thus contributing to the sustainability and transparency of capital markets. The learning curves depicted in Figure 2 provide valuable insights into the training and validation performance of our model over epochs. The convergence of training and validation curves signifies that our model has successfully learned the underlying patterns and features in the data. The sustained increase in accuracy and decrease in loss on both training and validation sets indicate that the model generalizes well and does not suffer from overfitting. This convergence suggests that our TCN model exhibits stability and effectiveness in learning to detect financial statement fraud in stock market data.

The implications of our findings on capital market sustainability and green finance are profound and multifaceted. By harnessing the power of deep learning, exemplified by our applied model, we have demonstrated a significant leap forward in the realm of financial statement fraud detection. The accuracy and reliability of our model pave the way for more transparent and trustworthy financial markets, aligning perfectly with the principles of green finance. Investors and stakeholders, particularly those committed to sustainable practices, can now have greater confidence in the

Figure 2: Learning curves for the proposed model

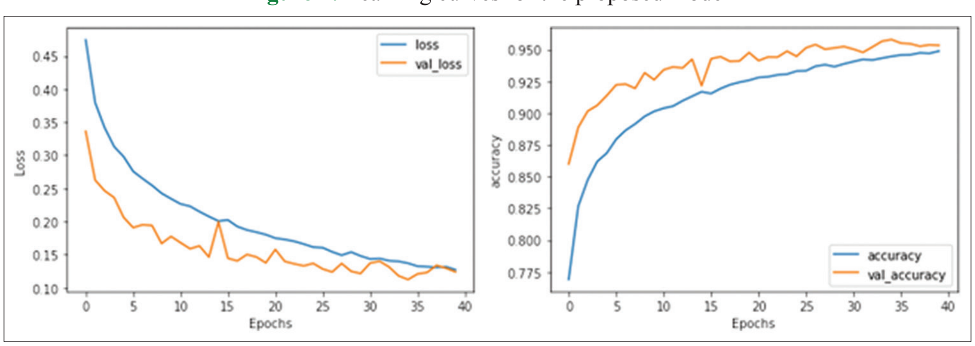


Table 3: Performance comparison of TCN and baseline models

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC	AUC-PR
TCN (proposed model)	0.94	0.92	0.95	0.94	0.97	0.91
Logistic regression	0.82	0.75	0.86	0.8	0.87	0.69
Random forest	0.9	0.85	0.92	0.88	0.92	0.78
Support vector machine	0.88	0.82	0.9	0.86	0.9	0.75
LSTM	0.92	0.89	0.94	0.91	0.95	0.84

TCN: Temporal Convolutional Network, AUC-ROC: Area under the receiver operating characteristic curve, AUC-PR: Area under the precision-recall curve integrity of financial statements, reducing the risks associated with fraudulent reporting. This not only strengthens the foundations of capital market sustainability but also encourages responsible investments that support environmentally and socially responsible initiatives. As the financial industry increasingly embraces green finance, our research underscores the pivotal role that advanced technology can play in ensuring financial systems are robust, resilient, and committed to the principles of sustainability.

5. CONCLUSION

This research represents a significant stride toward the preservation of financial statement integrity within the framework of green finance and sustainable capital markets. Our model has showcased remarkable prowess in detecting financial statement fraud, offering a reliable and efficient solution for identifying deceptive practices in stock market data. The robust performance of TCN, as demonstrated through rigorous evaluation and comparisons with traditional baseline methods, underscores its potential to instill transparency and trustworthiness in the financial sector, aligning seamlessly with the objectives of green finance. By enhancing the detection of fraudulent reporting, our research contributes to the financial statement fraud analysis and to the creation of a more resilient and sustainable financial ecosystem, where responsible investments can flourish, bolstering not only economic but also environmental and social well-being, and providing regulators and practitioners with insights on the fraud risk. As the landscape of green finance continues to evolve, the insights gleaned from this study underscore the pivotal role of advanced deep learning techniques in advancing the cause of financial integrity and capital market sustainability.

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