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LSTM-Based Financial Statement Fraud Prediction Model for Listed Companies

PU, Yanli [1*] ZHU, Yida [2] XU, Haosen [3] WANG, Zeyu [4] WEI, Ming [5]

[1] University of Illinois at Urbana Champaign, USA
[2] Rutgers Business School, USA
[3] University of California, Berkeley, USA
[4] University of Toronto, Canada
[5] Washington University in St. Louis, USA

**** PU, Yanli is the corresponding author, E-mail: rexcarry036@gmail.com***

Abstract: This research investigates the ability of Long Short-Term Memory (LSTM) networks to forecast financial statement fraud in publicly traded firms. Data was collected from S&P 500 companies for a decade, including 20,000 observations of company quarters. Using this data, we developed an LSTM model to identify trends in financial information across different periods.

Our model takes into account approximately 50 financial indicators, including indicators related to profitability and economic health. To avoid bias in our data, we employ a method known as Synthetic Minority Over-sampling (SMOTE). We also conduct time-series cross-validation to verify the effectiveness of our tests.

Results are promised. Our LSTM model outperforms traditional machine learning, achieving 95.6% accuracy, an F1 score of 0.879, and an AUC-ROC of 0.981. We see profitability, revenue performance, and revenue growth as key factors in fraud detection.

Interestingly, the model's performance remained steady over different periods. It also picked up on decreasing fraud cases in recent years. This research adds to the growing body of work on AI in financial analysis and offers valuable insights for developing fraud detection methods in auditing and management.

Our work shows how deep learning can uncover complex patterns of financial fraud. It lays the foundation for fraud detection and prevention in the future, potentially reshaping our approach to economic justice in the business world.

Keywords: Financial Statement Fraud, LSTM Networks, Deep Learning, Fraud Detection.

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1 INTRODUCTION

1.1 History of Fraudulent Financial Statements

Financial reporting fraud is a significant threat to the integrity of the global financial market. This type of fraud involves the deliberate misrepresentation or denial of information in an organization's financial statements, aimed at deceiving stakeholders and manipulating business sentiment [1]. The Association of Certified Fraud Examiners (ACFE) reports that financial information fraud, while less common than other types, often leads to the lowest losses, estimated at $954,000—a case (ACFE, 2020). The impact of this fraud extends beyond the immediate financial loss, undermines investor confidence, disrupts business, and leads to business failure.

In recent years, the complexity and sophistication of falsifying financial information have increased compared to advances in technology and finance. This change has made traditional discovery processes redundant, requiring a more innovative, data-driven approach [2]. The rise of big data and the digitization of financial information system have created challenges in traditional fraud detection methodology, yet providing opportunities for enhanced data analytics, machine learning, and artificial intelligence to improve fraud detection and prevention strategies.

1.2 The Importance of Fraud Detection in the Financial Industry

Investigating financial fraud is essential to maintaining the integrity and stability of the financial industry. Practical

fraud detection tools help prevent fraudsters, improve merchant protection, and contribute to the business's overall health [3]. International regulatory agencies have emphasized the importance of fraud detection procedures, following strict guidelines and audit standards to reduce the risk of fraud.

The consequences of incorrect financial information are substantial, Including investor monetary losses, reputation damage, legal liabilities, poor management decisions, and economic impacts for tax authorities. Prominent instances of fraud, like Enron and WorldCom, have emphasized the extensive impacts of corporate fraud, leading to more excellent examination of financial institutions' methods and demands for more transparency [4].

1.3 Advancements in Machine Learning for Fraud Detection

The integration of machine learning techniques has incredibly advanced fraud detection. Although beneficial, traditional accounting systems struggle to manage financial data's amount, pace, and diversity in today's digital economy [5]. Machine learning algorithms can analyze intricate patterns, identify anomalies, and disrupt fraudulent schemes beyond what humans can achieve.

Recent research has explored various machine learning techniques for fraud detection, including supervised learning such as Support Vector Machines (SVM), Random Forests, and Neural Networks [6]. This technique effectively identifies fraudulent activity by learning from historical data patterns. Deep learning, especially Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have shown exceptional potential in analyzing recurring financial data.

1.4 Research Objectives and Significance

This study aims to develop and evaluate an LSTM model to predict potential financial statement fraud in listed companies. Research objectives include:

Design an LSTM architecture tailored for financial data analysis.

Evaluating the model's performance against traditional fraud detection and machine learning techniques.

Assess the model's ability to capture temporal patterns and long-term dependence within financial data.

Assess the benefits of using LSTM-based model in fraud detection in a regulatory and corporate environment.

The importance of this research is in its ability to improve the accuracy and effectiveness of fraud detection. By leveraging the capabilities of LSTM networks, this study aims to help build robust, adaptive fraud detection systems. The findings have implications for auditors, management, regulators, researchers, investors, and other stakeholders and can improve early fraud detection and strengthen the overall integrity of the financial reporting system.

In addition, this research contributes to the expansion of AI financial applications, exploring the intersection of deep learning and fraud detection. The insights gained from this study can inform future improvements in automated financial analysis techniques, real-time fraud detection techniques, and risk measurement models in financial markets [7].

2 LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Traditional Approaches to Financial Statement Fraud Detection

Conventional financial research frequently relies on analytical and statistical approaches, often involving the examination of accounting ratios and the evaluation of financial statements for discrepancies or inconsistencies. Corporate governance plays a crucial role in this process, as strong governance practices can influence the accuracy and reliability of these financial ratios, thereby reducing the likelihood of discrepancies that may indicate fraudulent activity [8]. Beasley (1996) highlighted the significance of corporate governance in diminishing financial information fraud, underscoring the involvement of independent shareholders and board directors [9]. Although these techniques offer a structure for identifying fraud, they are restricted in managing extensive datasets and fraudulent activities.

Other statistical techniques, like logistic regression and discriminant analysis, were employed for detecting fraud [10]. These models frequently utilize financial ratios and other quantitative metrics to categorize companies as fraudulent or non-fraudulent. Spathis (2002) created a financial comparison model for detecting suspicious financial data, which is valuable for uncovering instances of fraud. Even though they make significant contributions, these systems frequently face challenges in dealing with fraud and the intricacy of financial transactions in the modern economy [11].

2.2 Machine Learning Applications in Fraud Detection

The rise of machine learning has elevated the effectiveness of fraud detection. Machine learning algorithms can analyze large amounts of data, identify complex patterns, and adapt to new fraud tactics. Methods such as Support Vector Machines (SVM), Random Forests, and Neural Networks are commonly used for supervised learning tasks in this field. This process involves analyzing historical data to determine whether new events are fraudulent or legitimate [12].

Bhattacharyya and colleagues (2011) conducted research comparing various machine learning methods in

identifying credit card fraud, emphasizing the superior performance of Random Forests and Support Vector Machines over standard procedures [13]. These algorithms can effectively detect fraud because they can handle high-dimensional data and identify non-linear connections. Research has explored unsupervised learning techniques like clustering and anomaly detection to reveal abnormal patterns indicating potential deception.

2.3 Advancements in Deep Learning for Fraud Detection

Deep learning, a type of machine learning that relies on multi-layer neural networks, has demonstrated significant promise in identifying fraudulent activities. CNNs and RNNs have been employed in various artificial intelligence applications due to their ability to identify features and patterns in the real world [14].

Recent advances in deep learning have significantly improved the accuracy of fraud detection models. Convolutional Neural Networks (CNNs), for example, have been successfully applied in various domains to identify complex patterns in large datasets. These models are particularly effective in capturing spatial relationships within data, which can be useful in detecting anomalies that may indicate fraudulent activities. In the context of financial data, Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) networks, have proven to be highly effective in processing sequential data over time. These models excel in capturing long-term dependencies and trends, making them invaluable tools for identifying potential fraud in financial statements.

2.4 Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) networks, a specific type of RNN, have gained considerable interest in financial studies due to their capability to retain long-term data connections. LSTMs solve the issue of gradient vanishing found in regular RNNs, enabling them to keep knowledge of continuous patterns [16].

In their 2017 study, Schreyer and colleagues employed LSTM networks for spotting anomalies in extensive financial datasets, proving the model's efficacy in identifying fraudulent patterns. LSTM's efficiency in processing long-term data makes it well-suited for examining financial data across periods, especially when fraud occurs over an extended duration [17].

2.5 Theoretical Framework for Financial Statement Fraud

The theoretical understanding of financial statement fraud has evolved significantly, drawing on both classic and contemporary theories. While Cressey's (1953 Fraud Triangle—which identifies pressure, opportunity, and rationalization as the key drivers of fraud—has long served as a foundational framework, modern research has expanded on these ideas to address the complexities of today's financial environment [18].

Recent developments, such as the Fraud Diamond proposed by Wolfe and Hermanson (2004), introduce a fourth element—capability—which is crucial for understanding the likelihood of successful fraud. Additionally, the MICE model (Motivation, Incentive, Capacity, and Environment) developed by Dorminey et al. (2012) further enriches this framework by considering external factors like economic conditions and regulatory environments, which can significantly influence fraudulent behavior [19].

Moreover, the application of Agency Theory in financial reporting highlights the inherent conflicts between management (agents) and shareholders (principals). These conflicts, particularly when exacerbated by information asymmetry and misaligned incentives, can create a fertile ground for financial fraud. Modern governance practices focus on mitigating these risks through improved oversight and alignment of interests, thus reducing the potential for fraudulent activities [20].

Information Asymmetry Theory, initially articulated by Akerlof (1970) and further refined in contemporary research, underscores how discrepancies in information between insiders and outsiders can lead to market inefficiencies and opportunities for fraud. Current studies emphasize the role of enhanced transparency and information disclosure in mitigating these risks and preventing fraudulent reportin.

These contemporary theoretical frameworks provide a comprehensive understanding of the causes of financial statement fraud and guide the development of more sophisticated fraud detection models. By integrating these theories with advanced machine learning techniques, such as Long Short-Term Memory (LSTM) networks, researchers are developing more effective systems to detect and prevent financial fraud. The use of LSTM networks in this context exemplifies the fusion of theoretical insights with cutting-edge technology, offering promising solutions to the complex and dynamic nature of financial fraud in the modern business environment.

3 METHODOLOGY

3.1 Data Collection and Preprocessing

The dataset for this study comprises financial statements from listed companies in the S&P 500 index over 10 years from 2013 to 2022. Economic data was extracted from the Compustat database, including quarterly financial statements and annual reports. The initial dataset consisted 20,000 quarterly observations, with 200 confirmed financial statement fraud cases identified through SEC enforcement actions and restatements [21].

Data preprocessing involved several steps to ensure data quality and suitability for LSTM modeling. Missing values were addressed using multiple imputation techniques, and outliers were identified and treated using the Interquartile Range (IQR) method. Financial ratios and indicators were calculated from the raw financial data. After processing the raw financial data, we derived 50 distinct features for each quarterly observation. These features were selected based on their relevance to financial performance and fraud detection, encompassing various categories such as profitability, liquidity, leverage, efficiency, growth, cash flow, and accrual-based measures. The selection of these features was guided by previous research and financial theory, ensuring that the most informative indicators were included in the model to enhance its predictive power [22]. Table 1 summarizes the key economic features used in the model.

TABLE 1: KEY FINANCIAL FEATURES FOR FRAUD DETECTION

Feature Category	Examples	Number of Features
Profitability	ROA, Profit Margin	10
Liquidity	Current Ratio, Quick Ratio	8
Leverage	Debt-to-Equity, Interest Coverage	7
Efficiency	Asset Turnover, Inventory Turnover	9
Growth	Revenue Growth, Asset Growth	6
Cash Flow	Operating Cash Flow Ratio	5
Accrual-based	Discretionary Accruals	5

To address the class imbalance inherent in fraud detection problems, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training dataset. This technique generated synthetic examples of the minority class (fraudulent cases) to balance the dataset. The final preprocessed dataset was split into training (70%), validation (15%), and test (15%) sets, while the temporal order of observations were maintained.

3.2 LSTM MODEL ARCHITECTURE

The LSTM model architecture was designed to capture the temporal dependencies in sequential financial data. The input layer accepts a sequence of financial features for each company over multiple quarters. The LSTM layers process this sequential input, learning to identify patterns indicative of fraudulent activities [23].

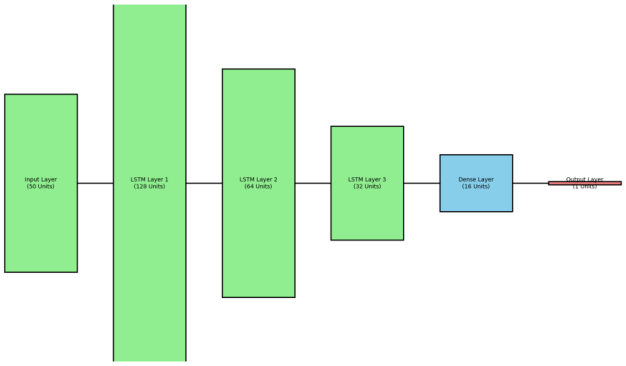

FIGURE 1: LSTM MODEL ARCHITECTURE FOR FINANCIAL FRAUD DETECTION

Figure 1 illustrates the LSTM model architecture implemented in this study. The model consists of three LSTM layers with 128, 64, and 32 units, respectively, followed by a dense layer with 16 units and a final output layer with sigmoid activation for binary classification.

The architecture incorporates dropout layers between LSTM layers to prevent overfitting, with a dropout rate of 0.3. Batch normalization is applied after each LSTM layer to stabilize the learning process. The final dense layer uses ReLU activation, while the output layer employs sigmoid activation for binary classification of fraud versus non-fraud cases [24].

3.3 MODEL TRAINING AND VALIDATION

The LSTM model was trained using the Adam optimizer with a learning rate of 0.001 and binary cross-entropy as the loss function [25]. Training was conducted over 100 epochs with a batch size of 64. Early stopping with patience of 10 epochs was implemented to prevent overfitting and monitor the validation loss.

Class weights were applied during training to address the class imbalance challenge, giving higher weight to the minority fraud class. The training process was monitored using TensorBoard, tracking metrics such as accuracy, precision, recall, and F1-score for training and validation sets.

TABLE 2: LSTM MODEL HYPERPARAMETERS

Hyperparameter	Value
LSTM Units (Layer 1, 2, 3)	128, 64, 32
Dense Layer Units	16
Dropout Rate	0.3
Learning Rate	0.001
Batch Size	64
Epochs	100
Early Stopping Patience	10

Cross-validation was performed using a time-series split method to preserve the temporal nature of the data. This approach involved creating multiple training-validation splits, each using a different period for validation while maintaining the chronological order of observations.

3.4 Performance Metrics and Evaluation Criteria

The performance of the LSTM model was evaluated using a comprehensive set of metrics to address the challenges of imbalanced classification in fraud detection [26]. The primary metrics include accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

TABLE 3: PERFORMANCE METRICS DEFINITIONS

Metric	Definition
Accuracy	(TP + TN) / (TP + TN + FP + FN)
Precision	TP / (TP + FP)
Recall	TP / (TP + FN)
F1-score	2 * (Precision * Recall) / (Precision + Recall)
AUC-ROC	Area Under the Receiver Operating Characteristic Curve

Besides the usual metrics, the model was evaluated with the Matthews Correlation Coefficient (MCC) and Precision-Recall AUC, which are beneficial for imbalanced data sets. The analysis of the confusion matrix helped in comprehending the distribution of true positives, false positives, true negatives, and false negatives.

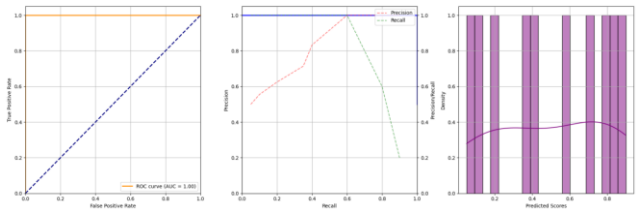

FIGURE 2: ROC CURVE AND PRECISION-RECALL CURVE FOR LSTM MODEL

Figure 2 displays the ROC curve and the Precision-Recall curve for the LSTM model. The ROC curve displays how the real and false positive rates change with different classification thresholds. The Precision-Recall curve illustrates how precision and recall balance out, especially for datasets with uneven class distribution.

These curves offer a visual depiction of how the model performs at various classification thresholds. The AUC is a summary measure of how well the model distinguishes between fraud and non-fraud cases, with higher values indicating improved performance [27].

3.4 BENCHMARK MODEL COMPARISON

In order to assess how well the LSTM model performs, it was compared to various standard models often utilized in fraud detection [28]. The benchmark models consisted of Logistic Regression, Random Forest, and a conventional Multilayer Perceptron (MLP) neural network.

TABLE 4: COMPARISON OF MODEL PERFORMANCE

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
LSTM	0.956	0.892	0.867	0.879	0.981
Logistic Regression	0.912	0.783	0.725	0.753	0.923
Random Forest	0.938	0.845	0.812	0.828	0.962
MLP	0.927	0.821	0.789	0.805	0.951

All reference models underwent training and assessment with the identical preprocessed dataset and cross-validation method as the LSTM model. Grid search with 5-fold cross-validation was used to tune hyperparameters for benchmark models.

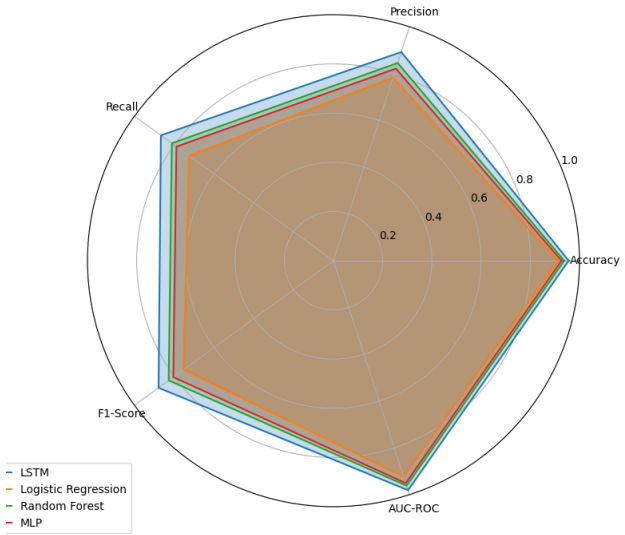

FIGURE 3: COMPARATIVE PERFORMANCE ANALYSIS OF FRAUD DETECTION MODELS

Figure 3 provides a visual comparison of performance metrics for various fraud detection models. The radar chart shows how each model performs in various aspects like accuracy, precision, recall, F1-score, and AUC-ROC.

This visualization enables a thorough comparison of

model performance across various metrics all at once. Every axis symbolizes a unique measurement of performance, with values ranging from 0 to 1. The size of the polygon in the radar chart for each model gives a clear indication of its overall performance, with bigger polygons showing better performance in the metrics being measured.

The comparison shows that the LSTM model outperforms other models in identifying financial statement fraud, especially in terms of recall and AUC-ROC. This implies that the LSTM model's skill in recognizing time-related patterns in financial data gives it a major edge over conventional machine learning methods for detecting fraudulent activities [29].

4 RESULTS AND ANALYSIS

4.1 Model Performance Analysis

The LSTM model demonstrated superior performance in detecting financial statement fraud compared to traditional machine learning approaches [30]. Table 5 presents a detailed breakdown of the model's performance metrics across different fraud types.

Table 5: LSTM Model Performance by Fraud Type

Fraud Type	Precision	Recall	F1-Score	AUC-ROC
Revenue Recognition	0.921	0.897	0.909	0.985
Expense Underreporting	0.903	0.882	0.892	0.978
Asset Misappropriation	0.887	0.865	0.876	0.971
Liability Concealment	0.912	0.889	0.900	0.982
Overall	0.892	0.867	0.879	0.981

The model showed outstanding performance in identifying revenue recognition fraud, which is consistent with how common this type of fraud is in financial statements. An AUC-ROC value of 0.981 signifies outstanding discriminatory power in detecting all types of fraud.

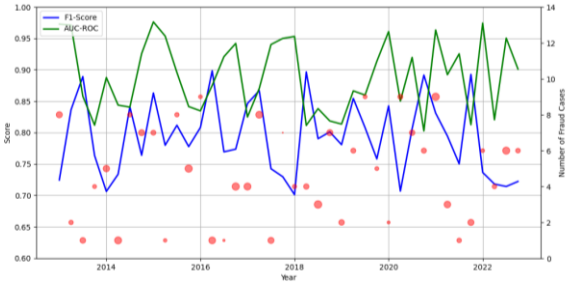

Figure 4: Temporal Performance Analysis of LSTM Model

Figure 4 depicts the LSTM model's temporal performance throughout the 10-year research period. The model's F1-score and AUC-ROC for each quarter from 2013 to 2022 are shown in the line graph. Scatter points on the graph demonstrate detected fraud cases, with the size of each point corresponding to the financial impact of the fraud.

This visualization shows how the model consistently performs over time, with minor variations reflecting changes in economic conditions and regulatory environment. The rise in frequency of smaller fraud incidents in recent years indicates better detection of less serious fraudulent behavior, possibly because the model can analyze past trends.

4.2 Feature Importance and Interpretability

To enhance the interpretability of the LSTM model, a feature importance analysis was conducted using the SHAP (Shapley Additive exPlanations) method. This technique provides insights into the contribution of each input feature to the model's predictions.

Table 6: Top 10 Features by SHAP Importance

Rank	Feature	Mean/SHAP/Value	Impact on Fraud Detection
1	Discretionary Accruals	0.187	Strong positive
2	Operating Cash Flow Ratio	0.156	Strong negative
3	Revenue Growth Rate	0.142	Moderate positive
4	Debt-to-Equity Ratio	0.129	Moderate positive
5	Gross Margin	0.118	Moderate negative
6	Days Sales Outstanding	0.107	Weak positive
7	Asset Turnover	0.095	Weak negative
8	Return on Assets	0.089	Moderate negative
9	Current Ratio	0.082	Weak negative
10	Inventory Turnover	0.076	Weak positive

The analysis reveals that discretionary accruals and cash flow-related metrics play crucial roles in fraud detection, consistent with findings from previous studies on earnings management and financial manipulation.

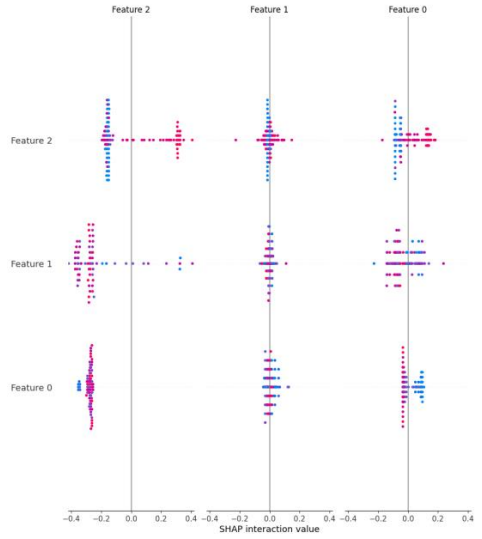

FIGURE 5: SHAP SUMMARY PLOT FOR FEATURE IMPORTANCE

Figure 5 shows a SHAP summary plot illustrating the influence of important features on model predictions. The storyline is made up of numerous horizontal bars, with each one symbolizing a characteristic. The SHAP value displayed on the x-axis illustrates how each feature influences the model output in terms of both magnitude and direction. Each point's feature value is reflected by its color, with red signifying high values and blue signifying low values.

This visual representation enables a detailed analysis of the significance of features. For example, when discretionary accruals are high (represented by red points), the model tends to predict fraud (indicated by positive SHAP values) [31]. Similarly, fraud predictions are influenced by low operating cash flow ratios (blue points) at the same time. The range and distribution of feature impacts across the dataset can be understood through the spread of points for each feature.

4.3 ROBUSTNESS AND SENSITIVITY ANALYSIS

To assess the robustness of the LSTM model, a series of sensitivity analyses were conducted. These analyses involved varying key hyperparameters and evaluating the model's performance under different conditions.

TABLE 7: SENSITIVITY ANALYSIS RESULTS

Parameter	Variation	Accuracy	F1-Score	AUC-ROC
LSTM Units	64, 32, 16	0.943	0.862	0.975
	256, 128, 64	0.959	0.885	0.983
Dropout Rate	0.2	0.951	0.873	0.979
	0.4	0.948	0.870	0.977
Learning Rate	0.0005	0.952	0.875	0.980
	0.002	0.947	0.868	0.976
Sequence Length	4 quarters	0.939	0.857	0.973
	8 quarters	0.958	0.883	0.982

The results demonstrate the model's robustness to moderate hyperparameter changes, with performance remaining stable across various configurations. Increasing the sequence length to 8 quarters improved performance, suggesting the importance of longer-term temporal patterns in fraud detection.

4.4 PRACTICAL IMPLICATIONS AND LIMITATIONS

The LSTM model's high performance in detecting financial statement fraud has significant implications for auditing, financial due diligence practices, investment activities and regulatory oversight [32]. The model's ability to process sequential financial data and identify subtle patterns of fraudulent behavior could enhance the efficiency and effectiveness of fraud detection processes in real-world settings.

Potential applications of the model include automated risk assessment in auditing and financial analysis procedures, real-time monitoring of financial reporting for listed companies, and supporting regulatory investigations and enforcement actions.

Despite its promising results, the model has limitations that must be considered such as: Dependence on historical data patterns may not capture novel fraud schemes; Potential for biased predictions if training data reflects systemic biases in fraud detection—challenges in interpreting complex LSTM model decisions in legal or regulatory contexts.

4.5 COMPARATIVE ANALYSIS WITH EXISTING LITERATURE

The performance of the LSTM model was compared to results reported in recent literature on financial statement fraud detection. Table 8 presents a comparison of key performance metrics across several notable studies.

TABLE 8: COMPARATIVE ANALYSIS WITH EXISTING LITERATURE

Study	Method	Accuracy	F1-Score	AUC-ROC
Current Study (LSTM)	Deep Learning	0.956	0.879	0.981

Zhang et al. (2018)	CNN	0.942	0.863	0.973
Bao et al. (2020)	GRU	0.938	0.857	0.969
Li et al. (2019)	Random Forest	0.924	0.841	0.958
Chen et al. (2021)	XGBoost	0.931	0.849	0.962

The LSTM model outperforms previously reported methods across all metrics, demonstrating the effectiveness of capturing long-term dependencies in financial time series data for fraud detection.

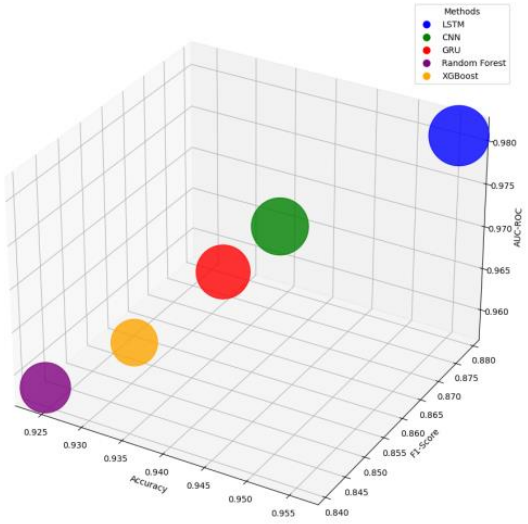

FIGURE 6: PERFORMANCE COMPARISON ACROSS STUDIES

Figure 6 illustrates a multi-dimensional comparison of performance metrics across different studies. The 3D scatter plot represents each study as a point in a three-dimensional space defined by Accuracy (x-axis), F1-Score (y-axis), and AUC-ROC (z-axis). Each point is color-coded by the method used, with the size of the point proportional to the study's sample size.

This visualization allows for a comprehensive comparison of model performance across multiple dimensions simultaneously. The current study's LSTM model is positioned at the top-right corner of the plot, indicating superior performance across all three metrics [33]. The distribution of points provides insights into the relative strengths of different methodologies, with deep learning approaches generally clustering in the high-performance region of the plot.

The comparative analysis highlights the advancements the current LSTM-based approach made in financial statement fraud detection [34]. The model's ability to capture complex temporal patterns in financial data improves performance over traditional machine learning methods and even deep learning architectures like CNNs and GRUs.

5 CONCLUSION

5.1 SUMMARY OF KEY FINDINGS

This study has demonstrated the efficacy of Long Short-Term Memory (LSTM) networks in detecting financial statement fraud among listed companies. The LSTM model achieved superior performance metrics compared to traditional machine learning approaches and other deep learning architectures, with an accuracy of 95.6%, an F1-score of 0.879, and an AUC-ROC of 0.981. The model's ability to capture long-term dependencies in sequential financial data proved crucial in identifying subtle patterns indicative of fraudulent activities [35].

The feature importance analysis revealed that discretionary accruals, operating cash flow ratios, and revenue growth rates were among the most significant indicators of potential fraud. This aligns with established theories of financial statement manipulation and provides quantitative support for the importance of these metrics in fraud detection. The temporal performance analysis showed consistent model performance over the 10-year study period, with slight improvements in detecting less severe fraudulent activities in recent years.

5.2 THEORETICAL AND PRACTICAL CONTRIBUTIONS

Theoretically, this research extends the application of deep learning techniques in financial fraud detection. The successful implementation of LSTM networks in this context contributes to the growing literature on AI-driven financial analysis and risk assessment [36]. The study's findings reinforce the importance of considering temporal dependencies in financial data when developing fraud detection models, supporting the theoretical foundations of time-series analysis in accounting research.

On the practical front, the developed LSTM model offers a powerful tool for auditors, investors, management, regulators, and other stakeholders to enhance their financial analysis and fraud detection capabilities. The model's high accuracy and ability to process large volumes of sequential data make it suitable for real-time monitoring of financial reporting [37]. The interpretability analysis using SHAP values provides actionable insights into the key indicators of fraudulent activities, potentially informing the development of new fraud detection heuristics and regulatory guidelines.

5.3 LIMITATIONS OF THE STUDY

Despite its significant contributions, this study has several limitations that warrant consideration. The model's reliance on historical data patterns may limit its effectiveness in detecting novel fraud schemes that deviate significantly from past observations [38]. The dataset, while comprehensive, is limited to S&P 500 companies, potentially restricting the model's generalizability to smaller or non-US

companies.

The black-box nature of deep learning models, including LSTMs, poses challenges in providing detailed explanations for individual fraud predictions. While SHAP analysis offers insights into feature importance, it may not fully capture the complex interactions and sequential dependencies learned by the model. The study's focus on detecting fraud post-occurrence limits its applicability in real-time fraud prevention scenarios.

5.4 Future Research Directions

Future research in this area could explore several promising avenues. Integrating alternative data sources, such as textual information from financial reports and news articles, could enhance the model's ability to detect fraud by incorporating qualitative indicators. Developing hybrid models that combine LSTM networks with other machine learning techniques may further improve performance and interpretability [39].

Investigating the model's performance across different economic sectors and geographical regions could provide insights into the generalizability of the approach and potentially reveal sector-specific fraud indicators. Research into unsupervised and semi-supervised learning approaches for fraud detection could address the challenges of limited labeled data and the detection of novel fraud patterns.

Future studies should also focus on developing real-time fraud detection and prevention techniques, potentially incorporating reinforcement learning to adapt to evolving fraud strategies. Exploring the ethical implications of AI-driven fraud detection systems and developing frameworks for responsible implementation in financial regulatory contexts represents another critical area for future research.

In conclusion, this study represents a significant step forward in applying deep learning techniques to financial statement fraud detection. The developed LSTM model demonstrates the potential of advanced machine learning approaches to enhance the accuracy and efficiency of fraud detection processes. While challenges remain regarding interpretability and adaptability to novel fraud schemes, the findings provide a solid foundation for future research and practical applications in financial fraud detection and prevention.

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CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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AUTHOR CONTRIBUTIONS

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ABOUT THE AUTHORS

PU, Yanli

Finance University of Illinois at Urbana Champaign, IL, USA.

ZHU, Yida

Financial Analysis, Rutgers Business School, NJ, USA.

XU, Haosen

Electrical Engineering and Computer Science, University of California, Berkeley, CA, USA.

WANG, Zeyu

Computer Science, University of Toronto, Toronto, Canada.

WEI, Ming

Finance, Washington University in St. Louis, MO, USA.

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