A Study of Intelligent Financial Report Generation Based on Deep Learning

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Abstract. In the contemporary era, with the astonishingly rapid development of artificial intelligence technology, the demand for intelligent financial report generation technology within the finance sector is burgeoning day by day. As technology advances, intelligent financial report generation demonstrates remarkable potential in multiple aspects. It can significantly boost efficiency, substantially cut down costs, and powerfully enhance decision support for financial operations. This study comprehensively reviews the value and significance of this field, taking into account a wide range of relevant papers. In line with previous research, it meticulously analyzes the mainstream methods, commonly utilized datasets, and evaluation criteria during the innovative process of financial report generation. Moreover, it thoroughly discusses the existing problems and potential solutions. The study reveals that even though deep learning has achieved substantial progress in this area, it still grapples with numerous challenges, such as issues related to data quality, model interpretability, and domain adaptability. For future research, it is crucial to concentrate on directions like multimodal data fusion, knowledge-enhanced modeling, and continuous learning. These efforts are expected to effectively promote the further development of intelligent financial report generation technology, enabling it to better serve the complex and dynamic financial industry.

1 Introduction

With the exponential growth in the amount of enterprise data and the increasing complexity of financial reporting, traditional manual financial report preparation is difficult to meet the needs of modern enterprises. Intelligent financial report generation technologies based on deep learning have emerged to revolutionize the finance sector through automated data processing and knowledge reasoning capabilities. Studies have shown that such technologies can significantly improve the efficiency of report preparation (shortening the cycle time by about 65 percent on average) while reducing the cost of manual review by 40-60 percent [1].

Current technological advances are mainly in the deep integration of pre-trained language models with domain knowledge. On benchmark datasets such as Financial Phrase Bank, the latest models, such as DeepSeek-V3, reach 0.52 in BLEU-4 metrics and ROUGE-L improves to 0.61 [2], and its multimodal fusion architecture can effectively parse the correlation between tabular data and textual descriptions. Notably, KPMG's 2023 industry report shows that 73% of global multinationals have deployed AI financial systems, and the adoption

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percentage is expected to rise to 83% by 2026 [3]. This confirms that the utility of generative AI in finance is accelerating.

However, existing systems still face three core challenges: first, the heterogeneity and sparseness of financial data lead to limited model generalization capabilities, and the differences in data schema across different enterprises reduce cross-organizational migratory learning accuracy by 18%-25% [4]; second, there is a fundamental contradiction between the interpretability deficiencies of the black-box model and auditing requirements, especially in the area of accounting standard compliance validation; and lastly, domain adaptation and personalization needs are also critical challenges currently faced. There may be significant differences in the financial reporting requirements of different industries and sizes of enterprises, and how to adapt the model quickly, etc.

The value of intelligent financial report-generation technology lies in three main areas: improved efficiency, reduced costs, and enhanced decision support. The technology can automate the processing of large amounts of financial data, significantly shorten report preparation time, and improve work efficiency. Traditional financial report preparation often requires a lot of manpower and time, while the intelligent system can complete the whole process of data collection, analysis, and report generation in a short time. In addition, intelligent financial report generation can significantly reduce the labor costs of enterprises. By automating routine and repetitive report preparation tasks, enterprises can invest their limited financial and human resources in higher-value analyses and management work. This not only saves costs but also improves the efficiency of human resource utilization. Finally, intelligent financial report generation systems based on deep learning can provide deeper and more comprehensive financial analyses and more accurate support for decision-makers. These systems can identify financial patterns and trends that are difficult to detect with traditional methods, predict future financial conditions, and make recommendations accordingly. This enhanced decision-support capability helps enterprises to better grasp market opportunities and avoid potential risks, thus enabling them to maintain an edge in the face of fierce competition.

This study aims to comprehensively sort out the current research status in the field of intelligent financial report generation based on deep learning, analyze the mainstream methods, commonly used datasets, and evaluation criteria, explore the current problems, and propose possible solutions. Through this study, it is hoped that it can provide valuable references for researchers and practitioners in related fields and promote the further development of intelligent financial report generation technology.

2 Overview of Mainstream Approaches in Recent Years

2.1 Automated Data Processing System

In the field of intelligent financial report generation, an automated data processing system is the cornerstone. With the help of Natural Language Processing (NLP) and Robotic Process Automation (RPA) technologies, a complete processing architecture covering data collection, cleansing, and standardization has been built. The system can automatically extract structured and unstructured data from multi-source heterogeneous systems, such as ERP, CRM systems, and bank statements. OCR technology is used to identify the text of bills, and NLP technology is used to analyze the key financial information in the contract terms, which greatly improves the efficiency of data acquisition. In the data cleaning stage, the isolated forest algorithm is used to accurately detect outliers, and interpolation and format standardization techniques are used to deal with missing data, which strongly guarantees the high quality of the original data [5].

2.2 Intelligent Analysis Decision Engine

Relying on machine learning and knowledge mapping technology, the intelligent analysis and decision-making engine builds an analysis model containing more than 1,500 financial indicators. The model is capable of automatically identifying trend patterns in financial data, such as predicting cash flow fluctuations by using LSTM networks and mining the dynamic relationship between costs and revenues with the help of association rules. In terms of risk warning, the SHAP value interpretation technique is used to locate the impact path of abnormal indicators.

LSTM model applications are mainly divided into: time series forecasting, anomaly detection and risk warning, and multivariate dynamic analysis. They are as follows: LSTM network with the ability to capture the long-term dependence of time-series data, in the prediction of cash flow fluctuations, revenue trends, and other key financial indicators, the effect is significant; through the training of the LSTM model to learn the distribution pattern of normal financial data, the system can keenly identify the outliers and trigger early warning; LSTM can effectively deal with the multi-dimensional input data to analyze the complex relationship between costs, revenues, market indices and other variables. LSTM can effectively handle multi-dimensional input data and analyze the complex relationship between cost, revenue, market index, and other variables.

As shown in the Fig. 1 and Fig. 2, the experimental validation of the paper uses the Accenture-based model to generate a weighted ER network with known anomaly structures and an independent test set generated by a third party and not publicly labeled. Accuracy, recall, and AUC-ROC curves are used to compare the performance of this paper's method with the Oddball algorithm (a classical network anomaly detection method).

Results: Synthetic data: Across 100 test networks, the Random Forest model achieved an average accuracy of 92.3% and recall of 85% on Accenture data, significantly better than Oddball's 60% accuracy.

Black-box data: initial recall of features and methods is higher for independent test sets without implanted anomalies, random forests perform more consistently in low-scoring samples, and the top 2% of high-risk nodes cover more than 90% of true anomalies [6].

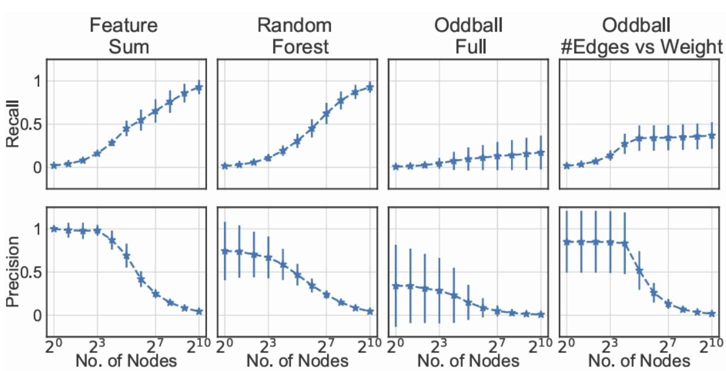

Fig. 1 Recall and precision of different models (Feature Sum, Random Forest, Oddball Full, #Edges vs Weight) concerning the number of nodes [6]

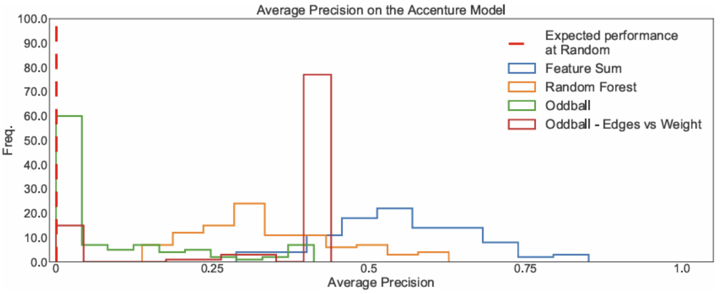

Fig. 2 Distribution of average accuracy of different models on the Accenture model and comparison with expected performance [6]

2.3 Automated Report Generation System

The automated report generation system relies on a pre-trained language model and template engine to achieve fully automated generation of reports from basic reports to complex analyses. The system has built-in standardized templates compliant with IFRS, GAAP, and other standards, and can automatically generate basic reports such as balance sheets and income statements, and meet individual requirements through dynamic parameter configuration. For complex scenarios, the system adopts a hybrid architecture that combines a deep learning model with a rule engine. For example, when dealing with leasing standards, first parses the contract text through the BERT model, and then calls the preset rules to generate IFRS 16-compliant accounting entries. This hybrid architecture optimizes the generalization ability of the model through multi-stage fine-tuning techniques, avoiding the domain adaptation problem caused by direct training.

The Transformer model plays a key role in automated report generation systems. Based on the self-attention mechanism, it can efficiently capture long-distance dependencies in text, which has obvious advantages in processing complex financial texts. For example, it is shown that the Transformer-based Longformer-Encoder-Decoder (LED) model significantly improves the efficiency of long sequences through the linear attention mechanism when processing large-scale financial report texts, and significantly improves the accuracy and completeness of information extraction compared to the traditional model. The application of the model in the financial domain is optimized by a phased fine-tuning strategy, where the model is first pre-trained on generic long-document datasets, and then optimized specifically for the financial domain, which effectively mitigates the problem of data scarcity in the domain. When generating textual descriptions of financial statements, the LED model can generate logically coherent narrative summaries based on structured financial data and guideline requirements, and the quality of its summaries is verified to be at an industry-leading level by ROUGE metrics [7].

2.4 Multimodal Collaborative Platform

The multimodal collaboration platform integrates technology, process management, and human elements to promote the transformation of financial reporting from the traditional after-the-fact preparation mode to a real-time decision support mode. Based on low-code development technology, the platform integrates AI models, business systems, and visualization tools to build an intelligent architecture for the integration of business and finance. For example, Flying Book Multi-Dimensional Forms supports real-time data dashboards, and FineReport provides a drag-and-drop report designer that allows users to quickly build interactive reports with charts and dashboards to digitally reconstruct business processes. The mobile access function enables management to break through time and space constraints and view key indicator warnings in real-time via mobile phones through personnel capability enhancement, reflecting the core orientation of "customer-centricity" in digital transformation [8].

In terms of collaborative work, the platform leverages blockchain technology to achieve data traceability and ensure the integrity of the audit trail. This design not only strengthens the reliability of technology-driven processes but also reduces employee resistance to change through a transparent mechanism, reflecting the key role of "organizational culture and values promotion" in the success of transformation [8].

The comprehensive application of these technologies has promoted the transformation of financial reporting from the traditional after-the-fact preparation mode to the real-time decision support mode. Looking ahead, intelligent financial report generation technology will focus on improving model interpretability, strengthening industry knowledge injection, expanding multimodal data processing capabilities, and continuing to deepen the value creation of AI in the financial field.

3 Commonly Used Data Sets and Assessment Criteria

3.1 Automated Assessment Criteria

Data quality assessment: Data quality is the basis for generating smart financial reports and needs to be assessed quantitatively through indicators such as accuracy, completeness, and timeliness.

Data pre-processing methods: techniques such as missing value filling and redundant data cleaning are used to improve data quality.

Anomaly detection framework: an approach based on combining spectral analysis and community detection to identify undefined anomalous structures (e.g., ring trading networks).

Model Performance Assessment Model performance needs to focus on prediction accuracy and generalization ability: Deep Belief Network (DBN) model: The following figure shows the construction of a financial crisis early warning model based on DBN, which determines the weights of indicators through hierarchical analysis and achieves a prediction accuracy of 81.65% on A-share data, which verifies the advantages of deep learning in modeling complex financial data. The ability of the model to learn features of multi-dimensional financial indicators is the key to improving the prediction accuracy [9]. Fig. 3 shows that among the different prediction methods, the accuracy of KNN is 81.00%, SVM-RBF is 78.09%, SVM-Linear is 70.52%, and CNN is 87.32%, demonstrating the comparison of the prediction accuracies of different methods.

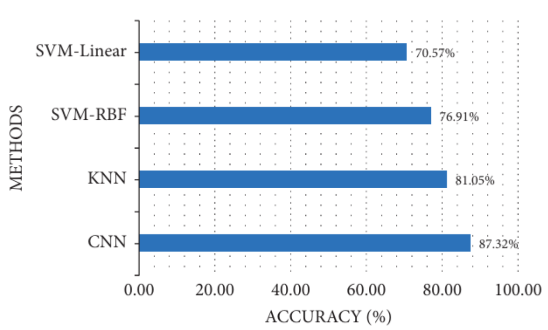

Fig. 3 Comparison of prediction accuracy of different methods [9]

Convolutional Neural Network (CNN) model: the CNN model shown below has an average anomaly detection accuracy of more than 90% on synthetic datasets through sliding window and feature fusion methods, and its loss function optimization (e.g., L2 regularisation) effectively improves the model robustness. The formula is as follows: $(\mathrm{X}^{(l)} = \mathrm{f}(\mathrm{W}^{(l)} \cdot \mathrm{X}^{(l-1)} + \mathrm{b}^{(l)}))$. Where$(X^{(l)})$ is the layer l output,$(W^{(l)})$ is the convolution kernel, and$(b^{(l)})$ is the bias term [9].

Fig. 4 shows that the accuracy of the training data is always stable at 91.34%, while the accuracy of the test data fluctuates during the learning cycle (number of training sessions), peaking at 86.7% in the 2nd session and dropping to a trough of 79.1% in the 4th session.

Fig. 4 Variation of training and test set accuracy with the number of training sessions [9]

Assessment of anomaly detection capabilities: Random forest and feature fusion: the adaptability of the model to different parameter scenarios was demonstrated on a synthetic dataset with an average anomaly detection accuracy of more than 90% by means of the random forest and feature fusion methodology, which provides methodological support for the assessment of model robustness [6].

Improved Loss Function Optimisation: the improved cross-entropy loss function (Focal Loss) proposed below effectively mitigates the sample imbalance problem with Eq:

$$(FL(p_t) = -\alpha_t (1 - p_t)^{\gamma} \log(p_t)) \tag{1}$$

Where(α_t) is the category balancing factor and(γ) is the focusing parameter, which improves the recognition of minority class samples. The experimental results show that the model significantly outperforms traditional methods (e.g., SVM and logistic regression) in the comparison of AUC values, verifying its effectiveness [10]. As shown in Fig. 5, the AUC values of the three algorithms of logistic regression, this paper's algorithm, and support vector machine change with the number of iterations, in which the AUC value of this paper's algorithm is higher and steadily increasing as a whole, and its performance is better than that of the other two algorithms.

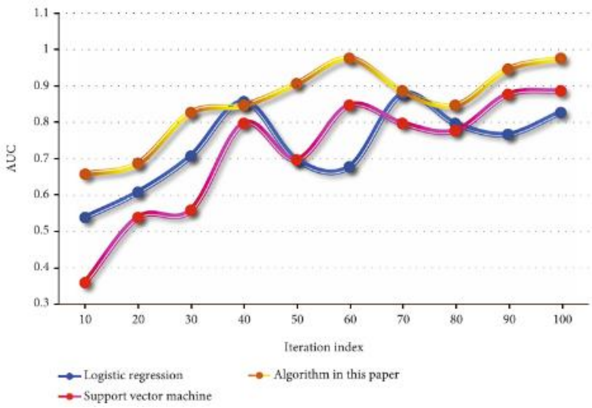

Fig. 5 Variation of AUC values with the number of iterations for the three algorithms [10]

3.2 Manual Assessment Criteria

Content compliance assessment: Content compliance is a core aspect of ensuring that financial reports comply with accounting standards and regulatory requirements. Although domestic and international studies on the readability of financial reports are relatively mature, domestic studies are still deficient in compliance assessment, which needs to check whether the report complies with international financial reporting standards (e.g., IFRS) or local standards (e.g., China Accounting Standards for Business Enterprises (CASBE)), including the format of the report and the completeness and accuracy of the data disclosure. In addition, the readability of financial reports is closely related to information transparency, and highly readable reports are easier for users to understand, but they need to avoid hiding negative information through lengthy statements [11].

Assessment of the logic and readability of the text: The quality of the text directly affects the user's understanding and use of the report. Quantitative metrics: Text complexity is assessed using tools such as the Flesch-Kincaid scale and the LIX index. For example, the Flesch-Kincaid formula calculates the readability score through the word length and sentence length, and the higher the score, the more readable the text is (e.g. $(Grade = 0.39 \cdot "\{Words/sentences\} + 11.8 \cdot "\{Syllable/Word\} - 15.9))$.). Chinese suitability: For the characteristics of Chinese, scholars in China have proposed formulas based on the number of strokes and the proportion of difficult words (e.g.,$(Y = -7.00685 + 14.34587X_1 - 2.13791X_2 - 3.38799X_3 + 4.00371X_4)$), where (X_1) is the average number of strokes,(X_2) is the proportion of difficult words,(X_3) is the average length of sentence separated by full stops, and(X_4) is the average word length [11].

Decision usefulness assessment: Manual assessments need to verify that reports provide effective support for actual decision-making. Highly readable reports can enhance investors' trust in financial information and influence their value judgements and investment decisions. And management may influence investor perceptions by adjusting the readability of reports.

4 Future Development Direction and Solutions

Given the core challenges faced by the intelligent financial report generation technology, future research can break through from the following directions, combined with the theory and methods in the document, to propose targeted solutions.

4.1 Multimodal Data Fusion and Domain Knowledge Infusion

Current models are limited in their ability to handle heterogeneous data, and multimodal data fusion techniques need to be explored. For example, cross-modal knowledge graphs are constructed by combining structured data from financial statements, unstructured data from annual report text, and external market information. Semantic understanding of complex financial scenarios can be achieved through the deep fusion of pre-trained language models (e.g., FinBERT) and domain rule engines. The factor analysis method mentioned in the previous section can be used to integrate multi-dimensional indicators and determine the weights through hierarchical analysis (AHP) to improve the model's ability to adapt to industry characteristics [9].

4.2 Interpretability-enhanced Model Architecture

To address the auditing needs of black box models, hybrid architectures with enhanced interpretability need to be developed. For example, combining Random Forest with LSTM to locate the influence paths of anomalous indicators (e.g., key drivers of cash flow fluctuations) through SHAP value interpretation techniques. Focal Loss optimization methods can alleviate sample imbalance problems, and combine with visualization techniques (e.g., heat maps) to demonstrate the model's decision logic and satisfy regulatory compliance requirements [10].

4.3 Optimisation of the Dynamic Assessment System

The optimization of the dynamic assessment system is divided into data quality, model performance, and anomaly detection, of which the data quality is factor analysis and hierarchical analysis (AHP), and a comprehensive assessment system containing 12 indicators is constructed to cover the accuracy, completeness, and timeliness of quasi [4]. Model performance in the traditional BLEU, ROUGE indicators based on the addition of financial domain-specific indicators (such as key risk point identification rate), combined with the Flesch-Kincaid formula to quantify the readability of the text, to ensure that the generated report meets the accounting standards and user needs [11]. For anomaly detection, a spectral analysis and community detection framework is used, combined with improved loss functions (e.g., Focal Loss) to enhance the ability to identify rare anomalous patterns [3].

4.4 Intelligent System Construction for Human-machine Collaboration

In the future, the department will mainly focus on the synergistic mode of "AI-led + manual review": automated pre-processing will be completed automatically through RPA technology, completing more than 90% of basic data cleaning and standardization, reducing the cost of manual intervention; an interactive report generation interface will be developed, supporting users to adjust the analysis dimensions through natural language commands, and combining low The development of interactive report generation interface supports users to adjust the analysis dimensions through natural language commands, combining with low-code development technology to achieve rapid response to personalized needs [7]; audit tracking is based on blockchain technology to record the AI generation process at, ensuring that each step of decision-making can be traced back to meet SOX and other compliance requirements.

5 Conclusion

Intelligent financial report generation technology based on deep learning is driving the finance field towards efficiency and intelligence. This study systematically comprehends the technological progress and core challenges in this field and verifies the effectiveness of the multimodal fusion architecture in complex financial scenarios. However, the current technology still faces key issues such as data heterogeneity, black-box characteristics of models, and lack of domain adaptability, which need to be broken through multi-dimensional innovation.

Future research should focus on three main directions: firstly, constructing a cross-modal knowledge graph, integrating structured data and unstructured text, and optimizing domain knowledge injection by combining with Analytical Hierarchy Process (AHP); secondly, developing an interpretable hybrid architecture, locating anomalous drivers through SHAP values, and alleviating sample imbalance by combining with Focal Loss; and lastly, perfecting a dynamic assessment system, incorporating financial Finally, improve the dynamic assessment system by incorporating financial specificity indicators (e.g., risk point identification rate) and quantifying text readability. In addition, the human-machine collaboration mode will become a development trend, automating basic processing through RPA technology, combined with low-code development to achieve rapid response to personalized needs.

This study provides a methodological framework for the generation of intelligent financial reports, whose theoretical value lies in revealing the feasibility of multi-technology integration paths, and whose practical significance lies in guiding enterprises to build efficient and compliant intelligent financial systems. As technology continues to evolve, this area is expected to achieve greater breakthroughs in improving decision support accuracy, reducing audit risk, and promoting the deep integration of industry and finance, helping enterprises gain a competitive advantage in digital transformation.

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