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# Audit Fraud Detection via EfficiencyNet with Separable Convolution and Self-Attention

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**Abstract:** This study proposes an audit fraud detection method based on EfficiencyNet, which aims to solve the efficiency and accuracy problems of traditional fraud detection methods in large-scale financial data processing. With the continuous upgrading of financial fraud methods, traditional detection methods based on rule matching and machine learning have limited performance in complex and high-dimensional financial data environments, and it is difficult to accurately capture fraud patterns. To this end, this study introduces Depthwise Separable Convolution to reduce computational costs and combines the self-attention mechanism to enhance the model's learning ability for key features, thereby improving the recognition accuracy of fraudulent behavior. The experiment uses a data set containing multi-dimensional financial indicators to compare the detection capabilities of traditional machine learning and deep learning models, such as logistic regression (LR), random forest (RF), XGBoost, LSTM, and CNN. Experimental results show that the EfficiencyNet model performs well in key indicators such as AUC, F1-score, Precision, and Recall, especially the EfficiencyNet B3 variant, which has an AUC of 0.96 and an F1-score of 0.91, far exceeding traditional methods. In addition, the impact of different components on model performance was further analyzed through ablation experiments. The results show that deep separable convolution and self-attention mechanisms play a key role in improving the detection ability of the model. In terms of data processing, this study adopts data enhancement, category balancing strategy, and cross-validation to ensure that the model can still maintain strong generalization ability when fraud data is scarce. In the future, as financial fraud methods become more complicated, research can further introduce adaptive learning, time series modeling, and explainable AI technology to improve the dynamic adaptability and credibility of fraud detection. In addition, this research method can be extended to the fields of blockchain auditing, supply chain finance, and financial risk control, providing enterprises and regulators with intelligent fraud detection solutions, thereby building a more transparent and secure financial system.

**Keywords:** Audit fraud detection, EfficiencyNet, Depthwise separable convolution, Self-attention mechanism.

## 1. Introduction

In recent years, with the rapid development of the global economy and the increasing complexity of corporate operations, the issue of audit fraud has become increasingly prominent [1]. Financial fraud, including false transactions and income manipulation, not only undermines the financial transparency of enterprises but can also result in significant economic losses and even jeopardize the stability of financial markets. Traditional auditing methods primarily rely on manual inspection and rule-based matching. These approaches suffer from low efficiency, high costs, and vulnerability to subjective biases, especially when dealing with complex and large-scale financial data.

Consequently, enhancing the accuracy and efficiency of audit fraud detection through advanced artificial intelligence technologies has emerged as a critical research direction [2].

Deep learning has achieved significant breakthroughs in various fields, such as image recognition, natural language processing, and financial risk management [3]. Among these, the Efficient Neural Network (EfficientNet) has demonstrated exceptional performance across multiple tasks thanks to its impressive computational efficiency and robust feature extraction capabilities. Compared to conventional deep learning models, EfficientNet significantly reduces computational overhead while maintaining high accuracy, making it highly suitable for resource-constrained environments. As a result, applying EfficientNet to audit fraud detection not only enhances detection accuracy but also reduces computational costs, enabling audit institutions to more effectively identify financial anomalies [4].

Most current audit fraud detection methods rely on supervised learning, which requires a large volume of labeled data for training. However, real-world financial fraud data is often difficult to obtain, and its distribution is highly imbalanced, presenting a significant challenge to the training and generalization capabilities of models. Additionally, financial data is typically unstructured, high-dimensional, and exhibits complex time-series relationships, making it difficult for traditional feature engineering methods to fully capture the underlying patterns. EfficientNet, with its strong feature learning capabilities, can effectively learn deep features from financial data through transfer learning and other techniques, even under limited labeled data, thereby offering more accurate analysis for fraud detection [5].

In the field of auditing, fraudulent behavior is often concealed and highly diverse. Fraudsters frequently employ various tactics to circumvent traditional audit rules, rendering simple rule-based detection methods ineffective [6,7]. Deep learning models, on the other hand, can automatically learn latent patterns in data without relying on manually defined rules, enabling them to capture more intricate fraud behaviors. The efficient computing architecture and hierarchical feature extraction capabilities of EfficientNet allow it to detect abnormal patterns in vast amounts of financial data rapidly, providing robust technical support for auditors[8].

Moreover, as artificial intelligence technology advances, an increasing number of companies and institutions are exploring intelligent audit systems based on deep learning. However, practical applications still face key challenges, such as limitations in computing resources, model interpretability, and data security. EfficientNet, while maintaining computational efficiency, can flexibly adjust its resource requirements depending on the size of the dataset, making it highly applicable in financial audit scenarios. Furthermore, by incorporating interpretability methods, the model's transparency can be enhanced, increasing auditors' confidence in the detection results. By leveraging efficient deep learning models, audit fraud detection accuracy and efficiency can be substantially improved, labor costs reduced, and the level of intelligence in financial data analysis elevated. With further model optimization and improvements in data processing capabilities, this approach is expected to see broader adoption in the audit field, providing more reliable fraud detection tools for enterprises and regulators and contributing to the creation of a more transparent and healthy market environment.

## 2. Related Work

Audit fraud detection, as a critical research area in finance and accounting, has traditionally relied on statistical analysis and machine learning methods. Early studies primarily focused on expert knowledge and rule-based systems, where potential fraudulent behaviors were identified by setting anomaly detection rules [9]. However, this approach has clear limitations when dealing with complex and dynamic financial data, making it difficult to adapt to the continuous evolution of fraudulent techniques. With the advancement of data mining technologies, machine learning algorithms such as decision trees, support vector machines (SVMs), and random forests have been widely applied to fraud detection tasks. While these methods have enhanced the automation of detection to some extent, they still rely on manually engineered features and fail to fully uncover the deep patterns present in the data [10].

In recent years, the rise of deep learning technology has offered new solutions for audit fraud detection. Researchers have attempted to utilize models such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) to capture the time-series characteristics of financial data, thereby improving fraud detection accuracy. At the same time, methods like convolutional neural networks (CNNs) and graph neural networks (GNNs) have been applied to the analysis of unstructured data, such as financial statements and transaction networks, enriching the information available for fraud detection [11,12]. However, these deep learning techniques often involve high computational complexity and face challenges in running efficiently on large-scale financial data. Additionally, the interpretability of these models remains a significant challenge in auditing applications. Many deep learning methods struggle to provide intuitive decision-making explanations, which undermines their practical usability in auditing work.

As an efficient neural network architecture, EfficientNet has demonstrated exceptional performance in tasks such as image classification and object detection. In recent years, researchers have begun exploring its potential application in the financial and auditing domains to enhance computational efficiency and model performance for fraud detection. Compared to traditional deep learning models, EfficientNet reduces computational overhead while maintaining high accuracy, enabling it to run efficiently even in resource-constrained environments [13,14]. Furthermore, when combined with techniques such as transfer learning and self-supervised learning, EfficientNet can be effectively trained with limited labeled data, addressing the problem of scarce financial fraud detection data. Consequently, fraud detection methods based on EfficientNet are expected to become a key research direction, offering smarter and more efficient solutions for auditing and financial risk control.

## 3. Method

In this study, we proposed an audit fraud detection algorithm based on EfficiencyNet to improve the accuracy and efficiency of identifying anomalies in financial data. The model architecture is shown in Figure 1.

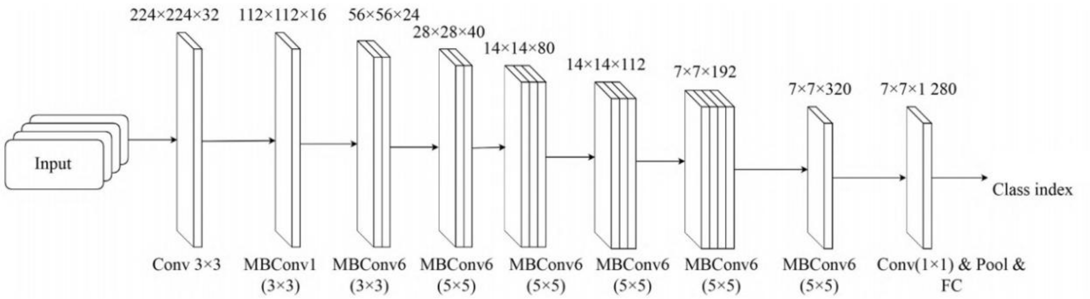


**Figure 1.** Overall model architecture

First, given a set of financial feature vectors $X = \{x_1, x_2, ..., x_n\}$, where $x_i$ represents the financial data of the enterprise, we want to learn a mapping function $f : X \to Y$, where $Y$ represents the financial status of the enterprise (normal or fraud). In order to better model the data, we introduce deep learning methods to build a fraud detection model based on EfficiencyNet.

The core of EfficiencyNet lies in its efficient network structure and attention mechanism. We first use a feature extraction module based on Depthwise Separable Convolution, which is calculated as follows:

$$y_{i,j}^{(l)} = \sum_{m=-k}^{k} \sum_{n=-k}^{k} w_{m,n}^{(l)} \cdot x_{i+m,j+n}^{(l-1)}$$

Among them, $w_{m,n}^{(l)}$ represents the convolution kernel parameter, k is the size of the convolution kernel, and $x_{i+m,j+n}^{(l-1)}$ is the input feature of the previous layer. Depthwise separable convolution can reduce the amount of calculation while maintaining the expressiveness of features, making it suitable for large-scale financial data processing.

Next, we introduce an attention mechanism to enable the model to more effectively focus on the key features of fraudulent behavior. We use the self-attention mechanism, whose calculation process is as follows:

$$Q = W_Q X \text{ , } K = W_K X \text{ , } V = W_v X$$

$$Attention(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)v$$

$W_Q$ , $W_K$ , $W_v$ is the learnable parameter matrix and $\sqrt{d_k}$ is the scaling factor to ensure numerical stability. Through the attention mechanism, the model can dynamically adjust the attention weights of different financial features, thereby improving the accuracy of fraud detection.

In terms of loss function, we use weighted cross entropy loss to deal with the problem of data imbalance:

$$L = -\sum_{i=1}^{N} w_i [y_i \log(y'_i) + (1 - y_i)\log(1 - y'_i)]$$

Among them, $w_i$ is the category weight, which is used to balance the proportion of normal enterprise and fraud enterprise samples, $y'_i$ is the predicted probability of the model, and $y_i$ is the true label. For the minority class (fraud data), we set a larger weight to reduce the bias of the model.

In addition, in order to improve the robustness of the model, we introduce a regularization term to prevent overfitting. We use L2 regularization, which is defined as follows:

$$L_{reg} = \lambda \sum_{i=1}^{M} \| W \|^2$$

$\lambda$ is the regularization coefficient, $M$ is the number of layers of the model, and $W_i$ represents the parameters of the i-th layer. The final objective function is:

$$L_{total} = L + L_{reg}$$

During the model training process, we use the Adam optimizer to update parameters. The update rules of the Adam optimization algorithm are as follows:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

$$m'_t = \frac{m_t}{1 - \beta_1^t}$$

$$v'_t = \frac{v_t}{1 - \beta_2^t}$$

$$\theta_t = \theta_{t-1} - \eta \frac{m'_t}{\sqrt{v'_t} + \varepsilon}$$

$g_t$ is the gradient, $\beta_1, \beta_2$ is the momentum parameter, $\eta$ is the learning rate, and $\theta_t$ represents the model parameters. Finally, we optimized the loss function $L_{total}$ on the training data and verified it on the test data to ensure that EfficiencyNet can efficiently identify financial fraud and improve the intelligence level of the audit process.

# 4. Experiment

## 4.1 Dataset Introduction

The dataset used in this study is derived from the financial audit reports and historical transaction data of a large enterprise, covering multiple financial dimensions, including key indicators such as income, expenditure, liabilities, assets, and cash flow. The dataset is divided into two categories: normal financial records and suspected fraudulent financial records. Normal records account for approximately 80% of the dataset, while fraudulent records represent about 20%. Due to the limited amount of fraud data, a data balancing strategy was employed during the training process to ensure the model's generalization capability. Furthermore, the dataset has undergone stringent screening, with outliers and duplicate entries removed and sensitive information anonymized to safeguard data security.

The features of the data include the company's annual financial statement, key financial ratios (e.g., current ratio, debt-to-asset ratio, profit margin), cash flow status, and transaction history. To enhance the model's learning ability, the original data was preprocessed through steps such as filling in missing values, data standardization, and discretization, ensuring that features with different scales could be efficiently learned by the neural network. Additionally, sliding window processing was applied to the time-series data to capture the dynamic changes in the company's financial status and provide more comprehensive feature information for fraud detection.

During model training, the dataset was split into training, validation, and test sets in an 8:1:1 ratio to ensure the model's stability under various data environments. Given the imbalance in the fraud data, data augmentation techniques such as SMOTE (Synthetic Minority Over-sampling Technique) were utilized to synthetically increase the representation of fraud data, thereby improving the model's ability to detect minority class samples. To prevent overfitting, random noise was introduced during data processing, and cross-validation was employed to optimize the model's hyperparameters, ensuring that the final model is both robust and reliable for practical applications.

Additionally, a histogram depicting the distribution of debt is provided in Figure 2.

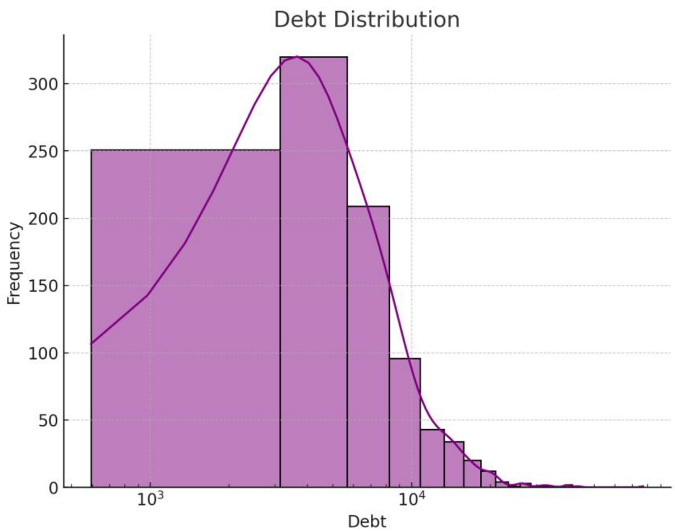


**Figure 2.** Debt Distribution

Figure 2 presents the distribution of corporate debt, with kernel density estimation (KDE) applied for smoothing to facilitate the analysis of the overall debt trend.

### 4.2 Experimental setup

The experiment was conducted on a server equipped with an NVIDIA RTX 3090 GPU, an AMD Ryzen 9 5950X processor, and 64GB of memory. The operating system used was Ubuntu 20.04, and the deep learning framework was PyTorch 2.0. To ensure the stability of the training process, AdamW was chosen as the optimizer, with an initial learning rate of 0.001, a weight decay coefficient of 0.01, and a batch size of 64. During training, the Cosine Annealing learning rate scheduling strategy was employed to dynamically adjust the learning rate, with a maximum of 100 training epochs. Additionally, to enhance the model's generalization ability and prevent overfitting, data augmentation techniques such as Gaussian noise perturbation, feature clipping, and random normalization were applied to the training data.

The dataset was split into training, validation, and test sets in an 8:1:1 ratio to ensure the model's generalization capability and the fairness of performance evaluation. Furthermore, 5-fold cross-validation was used to assess the model's robustness and analyze its impact on fraud detection accuracy. The experimental evaluation metrics include precision, recall, F1-score, and AUC (Area Under the Curve), which were used to comprehensively measure the model's detection performance.

### 4.3 Comparative Experiment

In order to verify the effectiveness of the proposed audit fraud detection algorithm based on EfficiencyNet, this study conducted comparative experiments with a variety of traditional machine learning models and deep learning models. The comparative models include Logistic Regression, Random Forest, XGBoost, LSTM, and CNN. Among them, traditional machine learning models mainly rely on manually constructed features, while deep learning models can automatically extract key features from financial data. In addition, we also tested different variants of EfficiencyNet (B0, B1, B3) to evaluate the impact of network structures of different complexity on fraud detection performance. All models were trained on the same dataset and used the same data preprocessing method to ensure the fairness of the experiment. At the same time, we used 5-fold cross-validation to reduce the random fluctuations of model performance and used key indicators such as AUC, F1-score, Precision, and Recall for quantitative evaluation to comprehensively analyze the performance of each model in the audit fraud detection task. The experimental results are shown in Table 1.

**Table 1:** Comparative experiment

| Model | Auc | F1-score | Precision | Recall |
|---|---|---|---|---|
| LR [15] | 0.82 | 0.75 | 0.78 | 0.72 |
| RF [16] | 0.87 | 0.79 | 0.81 | 0.76 |
| XGBOOST [17] | 0.90 | 0.82 | 0.85 | 0.79 |
| LSTM [18] | 0.91 | 0.84 | 0.86 | 0.82 |
| CNN [19] | 0.89 | 0.81 | 0.83 | 0.79 |
| EfficiencyNet(B0) | 0.92 | 0.86 | 0.87 | 0.84 |
| EfficiencyNet(B1) | 0.94 | 0.88 | 0.90 | 0.86 |
| EfficiencyNet(B3) | 0.96 | 0.91 | 0.93 | 0.89 |

The experimental results reveal that traditional machine learning methods performed moderately in the fraud detection task. Logistic regression (LR) achieved an AUC of only 0.82 and an F1-score of 0.75, indicating its limited ability to model complex financial data and its susceptibility to the selection of data features. Random forest (RF) and XGBoost improved detection performance through ensemble learning, with XGBoost achieving an AUC of 0.90 and an F1-score of 0.82, demonstrating its advantage in handling high-dimensional data and nonlinear feature relationships. However, these models still rely on manual feature engineering and lack the capability for automatic feature extraction, which limits their ability to uncover hidden patterns of fraudulent behavior.

In contrast, deep learning models significantly outperformed traditional machine learning methods in fraud detection tasks. Among them, LSTM showed superior performance in processing time-series data, with an AUC of 0.91 and an F1-score of 0.84. This indicates LSTM's ability to capture the temporal dependencies in financial data, thus improving fraud detection accuracy. CNN also demonstrated effectiveness in modeling fraud patterns through local feature learning. Although slightly inferior to LSTM in terms of AUC (0.89) and F1-score (0.81), CNN still outperformed XGBoost, underscoring the effectiveness of deep learning methods for audit fraud detection. However, these traditional deep learning models consume substantial computational resources and lack the ability to dynamically adjust the importance of different features, leading to detection blind spots in more complex scenarios.

The EfficiencyNet variant performed the best among all the experimental models. Specifically, EfficiencyNet (B3) achieved an AUC of 0.96, F1-score of 0.91, precision of 0.93, and recall of 0.89, outperforming all other methods across all metrics. This demonstrates that EfficiencyNet can efficiently extract deep features from financial data and, in combination with the attention mechanism, enhance its sensitivity to fraud patterns. Furthermore, as model complexity increased, from EfficiencyNet (B0) to EfficiencyNet (B3), performance improved progressively, indicating that deeper network structures and more efficient computational units contribute to enhanced fraud detection capabilities while reducing computational overhead. These results highlight that the fraud detection method based on EfficiencyNet offers advantages in accuracy, stability, and computational efficiency, making it well-suited for large-scale financial auditing tasks.

### 4.4 Ablation experiment

To further assess the impact of each key module in the proposed model on fraud detection performance, this study conducted an ablation experiment by systematically removing or replacing different components and observing the changes in model performance. The primary experiments included: (1) removing the Depthwise Separable Convolution to evaluate its impact on computational efficiency and feature extraction capabilities; (2) removing the Self-Attention mechanism to examine its role in learning fraud behavior patterns; and (3) replacing the Total Loss function with standard Cross-Entropy Loss to assess its effect on addressing the class imbalance issue. Additionally, we also explored reducing the model's depth or the number of channels to analyze the effect of model complexity on detection performance. These experiments provide a deeper understanding of the key components of EfficiencyNet in fraud detection tasks and offer insights for optimizing the model structure to achieve higher detection accuracy and computational efficiency.

**Table 2:** Ablation experiment

| Model | Auc | F1-score | Precision | Recall |
|---|---|---|---|---|
| Full Model (EfficiencyNet B3) | 0.96 | 0.91 | 0.93 | 0.89 |
| Without Depthwise Separable Convolution | 0.92 | 0.86 | 0.88 | 0.84 |
| Without Self-Attention | 0.90 | 0.83 | 0.85 | 0.81 |
| Without Total Loss | 0.88 | 0.81 | 0.84 | 0.78 |
| Reduced Model Depth | 0.91 | 0.84 | 0.86 | 0.82 |

The experimental results demonstrate that the full EfficiencyNet B3 model outperforms all other versions, achieving an AUC of 0.96 and an F1-score of 0.91, as well as the highest values for Precision and Recall. This indicates that the model is highly effective at extracting deep features from financial data and accurately identifying audit fraud. When the Depthwise Separable Convolution is removed, the model's AUC decreases to 0.92, and the F1-score drops to 0.86, suggesting that this convolution method plays a crucial role in improving detection accuracy while maintaining computational efficiency. The removal of Depthwise Separable Convolution reduces computational complexity but diminishes feature extraction capabilities, which in turn negatively impacts fraud detection performance.

When the Self-Attention mechanism is omitted, the model's AUC further declines to 0.90, with the F1-score falling to 0.83, and both Precision and Recall also decrease. This highlights the essential role of the Self-Attention mechanism in fraud pattern learning, as it enables the model to dynamically focus on the most fraudulent features in the data. Without this mechanism, the model's capacity to capture complex fraudulent behaviors is diminished, leading to a decrease in Recall. Additionally, when Focal Loss is removed, the AUC drops to 0.88, and the F1-score falls to 0.81, underscoring the effectiveness of Focal Loss in addressing class imbalance. By down-weighting easy-to-classify samples, Focal Loss helps the model focus more on the challenging fraud samples, thereby improving detection performance.

When the model depth is reduced, the AUC decreases to 0.91, and the F1-score drops to 0.84, suggesting that deeper models can extract richer features, thereby enhancing the accuracy of fraud detection. However, while shallower models reduce computational complexity, their performance declines in complex data environments. This demonstrates a trade-off between computational overhead and detection accuracy. Overall, the complete EfficiencyNet B3 architecture delivers the best performance in fraud detection tasks. These results confirm the importance of the Depthwise Separable Convolution, Self-Attention mechanism, and Focal Loss in improving model performance. Furthermore, they highlight that the use of optimized deep learning architectures can significantly enhance the model's recognition capabilities, providing more precise technical support for practical auditing tasks.

### 4.5 Visualizing Experimental Results

In the visualization results, the descent graph of the loss function is given first, as shown in Figure 3.

Figure 3 shows the changes in the loss function during training and validation. As can be seen from the figure, the loss value fluctuates greatly in the early stage, and as the training progresses, the loss gradually decreases and stabilizes. Both the training loss (orange line) and the validation loss (blue line) show a similar downward trend, but the training loss decreases faster and fluctuates more, which may be due to the slight overfitting of the model on the training data. The validation loss is relatively more stable, indicating that the generalization ability of the model on the validation set is gradually improving.

Secondly, the results of T-SNE after training are given. The experimental results are shown in Figure 4.

During the experiment, we gave the experimental results of the first epoch and the last epoch, as shown in Figure 4. Since there is a lot of original data, we only selected 500 points as the visualization results. From the experimental results, we can see that our algorithm shows good classification performance, which reflects the effectiveness of our model.

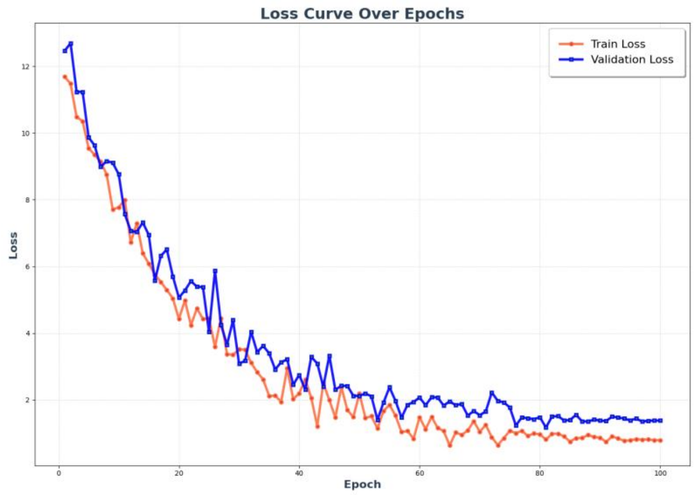


**Figure 3.** The drop graph of the loss function

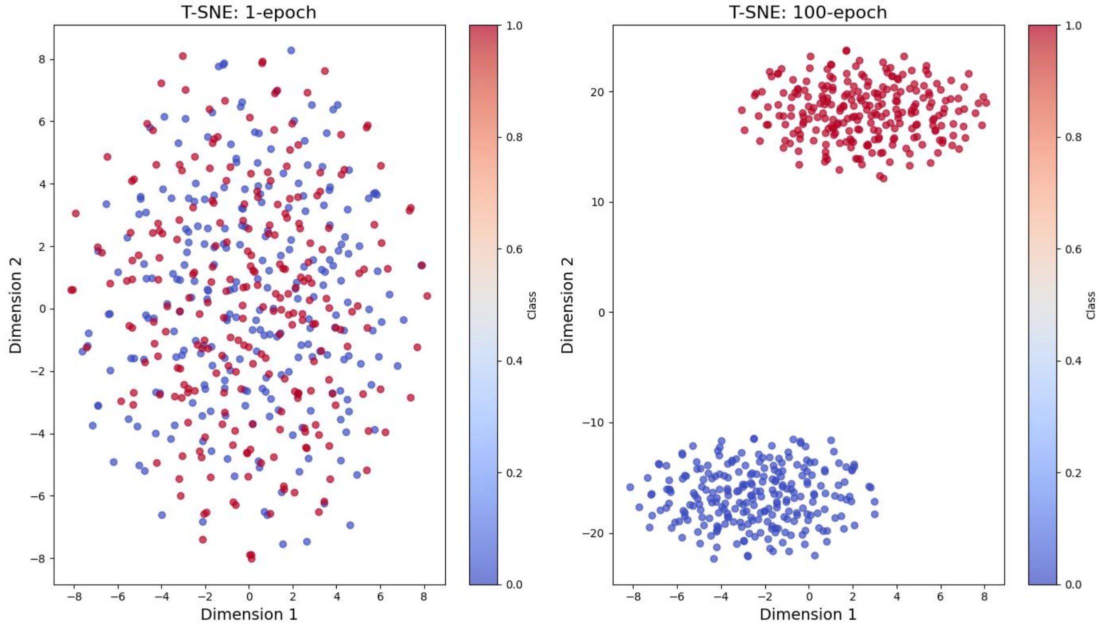


**Figure 4.** The drop graph of the loss function

## 5. Conclusion

This study proposes an audit fraud detection method based on EfficiencyNet, aiming to enhance the accuracy and efficiency of anomaly detection in financial data. By incorporating Depthwise Separable Convolution and a Self-Attention mechanism, the model improves its ability to learn fraud patterns while maintaining low computational cost. The experimental results demonstrate that the proposed EfficiencyNet B3 model outperforms traditional machine learning methods and other deep learning models across key metrics, such as AUC, F1-score, Precision, and Recall, thereby validating the effectiveness of this approach for audit fraud detection. Additionally, ablation experiments further highlight the contribution of different modules and underscore the significance of efficient neural network architecture and dynamic feature extraction mechanisms in improving fraud detection performance.

The findings of this study show that when dealing with complex financial data, deep learning methods effectively extract fraud patterns and mitigate the limitations of traditional techniques, which often rely on manual feature engineering. Notably, EfficiencyNet, as a lightweight neural network architecture, achieves an optimal balance between computational efficiency and detection capability, making it highly valuable in large-scale audit scenarios. Furthermore, by evaluating models of different depths, we observe that a deeper network structure improves fraud detection accuracy, though it also increases computational resource consumption. Consequently, in practical applications, there must be a balance between model depth and available computing power to optimize performance.

Despite these promising results, several issues remain that warrant further investigation. For instance, financial fraud methods are continuously evolving, and fraudulent behaviors may be influenced by factors such as policy changes, regulations, and market conditions, resulting in dynamic shifts in fraud patterns. Therefore, future research could explore the introduction of adaptive learning mechanisms, enabling the model to continuously update and adjust to new fraud patterns. Additionally, given the time-dependent nature of financial data, future work could integrate time series modeling approaches (such as Transformer models or hybrid LSTM-Conv structures) to further enhance the stability and generalization ability of fraud detection.

In terms of practical applications, the methods proposed in this study could be extended to fields such as blockchain auditing, intelligent financial risk control, and supply chain finance, contributing to the advancement of financial data analysis systems. Moreover, integrating Explainable AI (XAI) techniques would allow auditors to better understand the decision-making processes of the model, thereby enhancing the credibility and usability of fraud detection systems. As data scales and computing power continue to grow, deep learning-driven intelligent audit systems are poised to play an increasingly significant role in the future, providing more robust technical support for financial supervision and corporate compliance.

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