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Research Article

Enhanced Financial Fraud Detection via SISAE-METADES: A Supervised Deep Representation and Dynamic Ensemble Approach

Chang Wang [1,2] **Sheng Fang** [1,2] **Fangsu Zhao** [3] **and Zongmei Mu** [4]

[1] *School of Digital Economics and Management, Wuxi University, Wuxi 214105, China*
[2] *Institute of China (Wuxi) Cross-Border Electronic Commerce Comprehensive Pilot Zone, Wuxi University, Wuxi 214105, China*
[3] *School of Management, Chongqing University of Science and Technology, Chongqing 401331, China*
[4] *School of E-Commerce Logistics, Chongqing Business Vocational College, Chongqing 400030, China*

Correspondence should be addressed to Chang Wang; wangchang@cwxu.edu.cn

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Detecting financial reporting fraud is vital for preserving market integrity and protecting investors from substantial losses. Yet, the challenges of high dimensionality and noisy financial data often undermine the effectiveness of existing financial fraud detection systems. To address these issues, this study proposes SISAE-METADES, a novel framework that integrates a supervised input-enhanced stacked autoencoder (SISAE) with a meta-learning–based dynamic ensemble selection (METADES) strategy. Unlike conventional stacked autoencoders, SISAE concatenates the original input at each encoding stage and incorporates label supervision, thereby learning task-relevant and class-discriminative representations. These enriched deep features improve both the diversity and competence of base classifiers and enable METADES to achieve more reliable local competence estimation. We validate the proposed framework using financial statement data from Chinese A-share listed companies (2005–2023), covering 71 indicators. Experimental results show that SISAE-METADES significantly outperforms standalone SISAE, traditional METADES, and several state-of-the-art baselines. In particular, it achieves substantial improvements in accuracy, recall, and F1-score, underscoring the robustness and effectiveness of combining supervised deep representation learning with dynamic ensemble selection for financial fraud detection. These findings highlight the framework's practical significance in reducing investor losses, strengthening market confidence, and promoting the stability of the financial system.

Keywords: dynamic ensemble learning; financial fraud detection; meta-learning; SISAE-METADES; supervised autoencoder

1. Introduction

In today's complex and changeable financial market, financial fraud has emerged as a pressing issue. It not only inflicts direct economic losses on investors but also undermines market fairness and transparency, seriously eroding investor confidence and posing a threat to the stability of the entire financial system. For example, data from China Securities Regulatory Commission (CSRC) revealed that, from 2021 to 2023, CSRC addressed 397 illegal cases of information disclosure involving listed companies, including 203 cases of fraud. Financial fraud undermines the integrity of the capital market and seriously infringes on the legitimate rights and interests of investors [1, 2].

Given this challenges, the application of financial fraud detection models is crucial for regulators, company management, auditors, and investors [3]. With the rapid growth of big data and advancements in artificial intelligence, an increasing number of researchers are using sophisticated machine learning models to detect financial fraud [4, 5]. For example, classic machine learning models such as logistic regression, support vector machines (SVMs), and decision trees (DTs) have been applied in this field [6]. However, traditional fraud detection methods mainly rely on manually formulated rules or feature engineering, which require expertise and are very time-consuming to develop and maintain. Moreover, these methods often lack adaptability, making them ineffective in dealing with the increasingly complex and changing financial fraud behaviors. While these approaches have achieved some level of success, they face challenges in managing high-dimensional data, capturing nonlinear relationships, and identifying the complex patterns commonly found in financial fraud detection.

Deep learning approaches, particularly autoencoders (AEs), offer a compelling alternative for extracting meaningful low-dimensional representations from high-dimensional data [7, 8]. By compressing and reconstructing input data, AEs reduce redundancy and noise, thereby improving the performance of subsequent classifiers [9, 10]. Stacked autoencoders (SAE) extend this concept to multiple layers, enabling the learning of progressively more complex, nonlinear features [11]. Single-layer AEs have been utilized in financial market prediction models [12]. Nevertheless, techniques that employ SAEs yield highly complex predictors containing more valuable information. The greater the depth of the SAE, the more intricate the identified predictors become. The predictor at each layer is constructed through a combination of features generated by the preceding layer. Learning algorithms applied to SAEs are adjusted via layer-by-layer training and are beneficial for learning weights for deep SAEs [13]. However, conventional SAEs are typically unsupervised, optimizing for reconstruction rather than classification, which can limit their discriminative power in fraud detection tasks.

Ensemble learning techniques have also been widely used to improve generalization performance [14]. Dynamic ensemble selection (DES) further refines this approach by estimating each base classifier's competence for a given query and selecting the most appropriate subset for prediction. Among DES algorithms, METADES algorithm employs various individual-based criteria (such as probability, accuracy, and behavior) to evaluate whether the base classifier is capable of correctly classifying the test sample [15]. However, the accuracy of competence estimation heavily depends on the quality of the feature space in which it operates.

This paper addresses these limitations by introducing supervised input-enhanced SAE with the METADES (SISAE-METADES), a framework that integrates an SISAE with the METADES mechanism. Unlike conventional SAE, SISAE feeds the original input into each encoding layer and incorporates label supervision during training, producing task-relevant, class-discriminative features. These features both enhance the diversity and competence of base classifiers and improve METADES's local competence estimation, particularly for minority-class fraud cases.

In summary, this paper makes the following contribution:

- We propose SISAE-METADES, a synergistic integration of SISAE and METADES. SISAE's supervised, input-enhanced representations improve the diversity and competence of the METADES classifier pool and lead to more accurate dynamic selection.
- We design an enriched meta-feature set for METADES by combining multiple dynamic selection meta-vector $v_{ij} = \{f_1 \cup f_2 \cup f_3 \cup f_4 \cup f_5 \cup f_6 \cup f_7\}$ (such as local accuracy, posterior probability, classifier confidence, and fuzziness) with the feature calculations derived from SISAE, thereby forming a more structured and less noisy latent space.
- We validate SISAE-METADES on financial statement data from Chinese A-share listed companies (2005–2023). Extensive experiments and ablation studies show that it outperforms standalone SISAE, traditional METADES, and other state-of-the-art baselines in accuracy, recall, and F1-score.
- In general, this study makes a significant contribution to the field of financial fraud detection by introducing the SISAE-METADES framework, which integrates supervised input-enhanced representation learning with DES. The conclusions of this study lead to more accurate and timely identification of fraudulent financial reporting, thereby reducing investor losses, strengthening market confidence, and enhancing the overall stability of the financial system.

The rest of this paper is organized in the following manner. Section 2 examines the related work, whereas Section 3 describes the methodology. Section 4 shows the experimental results, and Section 5 draws the conclusion of the paper.

2. Related Work

2.1. Financial Statement Fraud Detection. Financial statement fraud refers to deceiving users of financial statements by correcting erroneous statements in order to make the organization appear beneficial [16]. The incentive to engage in fraud is to boost the stock price, acquire personal bank loans, lighten the tax burden, or draw in as many investors as possible [17]. In the big data era, numerous studies have put forward various methods for financial statement fraud, especially within the domain of machine learning algorithms. Specifically, Lin et al. utilized logistic regression, decision tree (CART), and artificial neural network (ANN) to detect financial statement fraud [18]. The study's outcomes reveal that ANN and CART offer superior accuracy compared to logistic models. In another comparative study, Ravisankar et al. employed logistic regression, SVM, genetic programming (GP), probabilistic neural network (PNN), multilayer feedforward (MLFF) NN, and grouped data processing method (GMDH) for predicting financial fraud [19]. Kirkos et al. explored the utility of DTs, NNs, and Bayesian belief networks (BBNs) in identifying fraudulent financial statements [20]. Cecchini et al. propose a SVM approach to detect managerial fraud using fundamental financial data [6]. An essential element of the method is a kernel specific to the financial domain, which enhances the learning machine's power by enabling implicit, often nonlinear, points to be mapped to a higher dimensional feature space. In the development of financial restatement prediction model, Dutta et al. use DT, ANN, Naive Bayes (NB), SVM and BBN classifiers and find that the recognition accuracy of ANN is better than other machine learning algorithms [21]. However, most of these approaches rely heavily on manually engineered features and static model structures, which limits their adaptability to evolving fraud patterns and their effectiveness when faced with high-dimensional, noisy, and imbalanced datasets.

2.2. Fraud Detection Based on AE. Traditional machine learning methods have difficulty in capturing the specific complex features of fraudulent transactions, which may limit their effectiveness in accurately detecting fraud. AEs are a type of NN architecture that learns to encode and decode input data, and the aim of AEs is to capture the most significant features and patterns in the data [22]. Based on the idea of AE, Chen et al. utilized a relationship model based on variational AEs (VAERM) to learn the patient–doctor relationship structure and improve the automatic detection of medical fraud in small datasets [23]. To distinguish fraud opinion, Dong et al. develop a hybrid model by combining neural decision forest with lightweight AE to detect fraud opinion [24]. In the insurance fraud detection field, Gomes et al. utilized AE to infer the complexity and dynamic changes of criminal behavior. Its data representation based on probability distribution can not only determine instances but also identify the driving factors of fraud [25]. Traditional AE usually employs a single-layer encoder, which makes it difficult to extract deep features. To enhance feature extraction, an effective strategy is to deepen the NN structure. By adopting a hierarchical learning method, multiple basic AEs can be stacked together to form a SAE, thereby enabling the extraction of complex data features. The training process of each individual AE involves learning a condensed data representation, and the final output is obtained by combining the outputs of these individual AEs. For example, El Hlouli et al. proposed a fraud detection framework that combines SAEs with kernel extreme learning machine (Kernel ELM) and used the dandelion algorithm for optimization. This method first performs deep feature extraction on transaction data using SAE and then uses Kernel ELM to complete the classification task, thereby improving the detection accuracy while maintaining computational efficiency [26]. Further, Abadlia and Smairi applied enhanced particle swarm optimization (EPSO) to the hyperparameter optimization of SAE to construct an efficient credit card fraud detection model. The key parameters in the SAE network structure, such as the number of hidden layers and the learning rate, are automatically selected through EPSO, effectively enhancing the model performance and convergence speed. This method demonstrates strong generalization ability and robustness on multiple real datasets, providing a feasible path for the practical application of SAE in financial scenarios [27]. While SAEs enhance feature extraction compared to shallow architectures, conventional SAE designs are typically unsupervised and reconstruction-oriented, which may yield latent features that are not sufficiently class-discriminative for fraud detection tasks in complex financial environments.

2.3. Financial Fraud Detection Based on Dynamic Selection Algorithms. As a branch of machine learning, the merits of ensemble learning have been demonstrated both experimentally and theoretically. Hansen and Salamon proved that a set of classifiers can produce more accurate prediction results than the optimal single classifier [28]. By combining the strengths of multiple classifiers suitable for different local regions, the drawbacks of each classifier can be offset by other members, thus guaranteeing the final prediction accuracy [1, 29]. Owing to the distinctiveness of diverse financial data, it is challenging for one classification algorithm to be applicable to all credit data sets. Therefore, ensemble methods—including random forest (RF), AdaBoost, stacking, gradient boosting decision tree (GBDT), XGBoost, and LightGBM —was widely used for financial fraud identification [30, 31]. Zhou et al. propose tree-based ensemble classifiers applied to a wide range of original financial statement datasets for fraud classification [32]. Song et al. propose an ensemble method to assess the risk of fraud in financial statements, which combines the prediction results of all the combined classifiers by voting and uses different weights to vote for the base classifier. The results show that the proposed ensemble of classifiers outperforms the four base classifiers in terms of accuracy and comprehensive error rate [33].

However, most of the ensemble methods mentioned are static in nature. Firstly, the effective classifiers are chosen based on their average performance on the validation set. Subsequently, all test samples are labeled by means of the same ensemble classifier [34]. An ensemble classifier selected in this manner might not display optimal performance on a single test sample. Therefore, it is essential to target each test sample according to its unique area of competence [35]. Although DES improves upon static ensembles by adapting classifier selection to individual samples, its competence estimation is often based on raw or shallow features and limited evaluation criteria, constraining its potential in detecting subtle and heterogeneous fraud patterns.

2.4. Remarks. Existing studies reveal three main gaps in financial statement fraud detection. First, conventional ML and unsupervised SAEs often fail to learn class-discriminative features from high-dimensional, noisy, and imbalanced data, limiting their ability to capture subtle fraud patterns. Second, most ensemble methods are static, neglecting per-sample variability, while current DES implementations rely on raw or shallow features, reducing competence estimation accuracy. Third, competence evaluation in DES is typically based on a single criterion, overlooking other indicators such as classifier confidence and ambiguity. To address these issues, we propose SISAE-METADES, integrating supervised input-enhanced SISAE with METADES and introducing multicriteria meta-features from deep representations, enabling more robust and adaptive fraud detection.

3. Methodology

A real-world financial market where financial reporting fraud occurs will cause significant losses to investors, which will involve multiple high-dimensional financial data features. In addition, since the data come from many financial reports, labeling many fraud cases will be very difficult, error-prone, and time-consuming. Therefore, for existing deep learning models to process this large amount of (mostly unlabeled) information, it is necessary to filter the numerical features, preferably using unsupervised learning methods. This is seen as an indispensable data processing step in building a fraud model [12, 36]. To address these challenges, we propose a two-stage fraud detection framework, SISAE-METADES. In the first stage, a SISAE is trained on available data to learn noise-resistant, class-discriminative features that compress the original feature space (Section 3.1). In the second stage, these deep representations are used to train a dynamic ensemble classifier based on the meta-learning paradigm, enabling adaptive selection of the most competent base classifiers for each sample (Section 3.2).

3.1. Financial Fraud Predictor Identification Using SISAE. To effectively detect financial fraud from high-dimensional, noisy, and imbalanced financial data, we adopt an unsupervised–supervised hybrid representation learning framework. The foundation of our approach is the AE, a NN that compresses input data into a lower dimensional latent representation and then reconstructs it. The encoder learns to capture the most informative patterns, while the decoder attempts to recover the original input. This basic structure, shown in Figure 1, is widely used for feature extraction and dimensionality reduction.

However, conventional AE often employ only a single hidden layer, limiting their capacity to model hierarchical and nonlinear dependencies among financial indicators. To address this, SAEs hierarchically stack multiple AE units, where each layer learns from the output of the previous one. This architecture enables progressively richer representations of the data, as illustrated in Figure 2. While SAE can extract deeper features, they are typically trained in a fully unsupervised manner, which may not yield features optimally aligned with fraud detection objectives.

In this study, we employ the SISAE and, to the best of our knowledge, adapt it for the first time to the task of financial fraud detection. The SISAE is a novel deep learning architecture designed to extract target-relevant hierarchical features, particularly suitable for high-dimensional financial data in fraud detection tasks [37]. Compared to conventional SAE, SISAE enhances feature representation by injecting both original inputs and supervised target information into each layer during training.

As shown in Figure 3, SISAE comprises three main components: an input layer, a hidden (encoding) layer, and a reconstruction (decoding) layer. When $l = 0$, the encoding

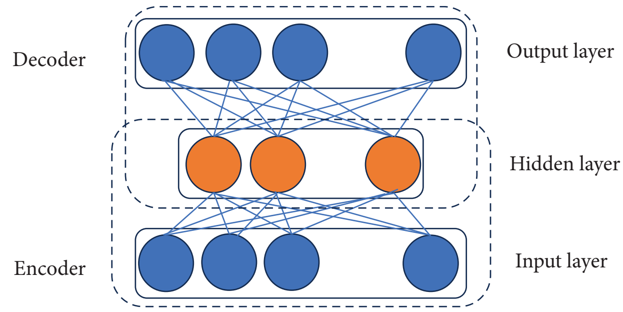


Figure 1: The framework of autoencoder.

process maps the input data $X \in \mathbb{R}^{n\times d}$ to a hidden representation $h^{(1)}$, as defined in equation (1):

$$h^{(1)} = f\left(W_e^{(0)} X + b_e^{(0)}\right). \quad (1)$$

For the decoder part, the hidden representation $h^{(1)}$ is decompressed to reconstruct X and y with parameter set $\{\widetilde{W}_d, \widetilde{b}_d\}$:

$$\left[\widetilde{X}, \widehat{y}^{(1)}\right] = f\left(\widetilde{W}_d^{(0)} h^{(1)} + \widetilde{b}_d^{(0)}\right). \quad (2)$$

After that, the original input $X\,(h^{(0)} = X)$ is concatenated with each intermediate hidden layer representation $h^{(l-1)}$ before being fed into the next encoder stage, thereby preserving raw feature information and mitigating the loss of discriminative signals during deep encoding. Generally, when $l = 1, 2, \ldots, L-1$, the hidden representation $h^{(l)}$ can be obtained as follows:

$$h^{(l)} = f\left(W_e^{(l-1)} \left[h^{(0)}, h^{(l-1)}\right] + b_e^{(l-1)}\right), \quad (3)$$

where W_e and b_e represent the weight matrix and bias vector for the encoder. This skip-connection-like mechanism ensures that raw input information is preserved and interactively combined with learned representations, enhancing feature robustness.

Unlike conventional SAEs that optimize only the reconstruction error, SISAE jointly minimizes reconstruction loss and classification loss:

$$\varepsilon_{\text{SISAE}} = \varepsilon_{\text{rec}} + \varepsilon_{\text{sup}}, \quad (4)$$

where $\varepsilon_{\text{SISAE}} = (1/n)\sum_{i=1}^{n}\|X_i - \widehat{X}_i\|_2^2$ is the reconstruction loss and $\varepsilon_{\text{sup}} = -(y \quad \log\widehat{y} + (1-y)\log(1-\widehat{y}))$ is binary cross-entropy. The training procedure of SISAE for financial fraud prediction can be summarized as follows:

- Step 1: We train the initial ISAE layer using the original input X, extracting the first-level feature representation $h^{(1)}$, while minimizing both reconstruction and prediction error.
- Step 2: For each subsequent ISAE layer >1, we feed both the original input X and the previous hidden representation $h^{(l-1)}$ into the encoder. The decoder reconstructs $\widetilde{h}^{(l-1)}$ and predicts $\widehat{y}^{(l)}$.

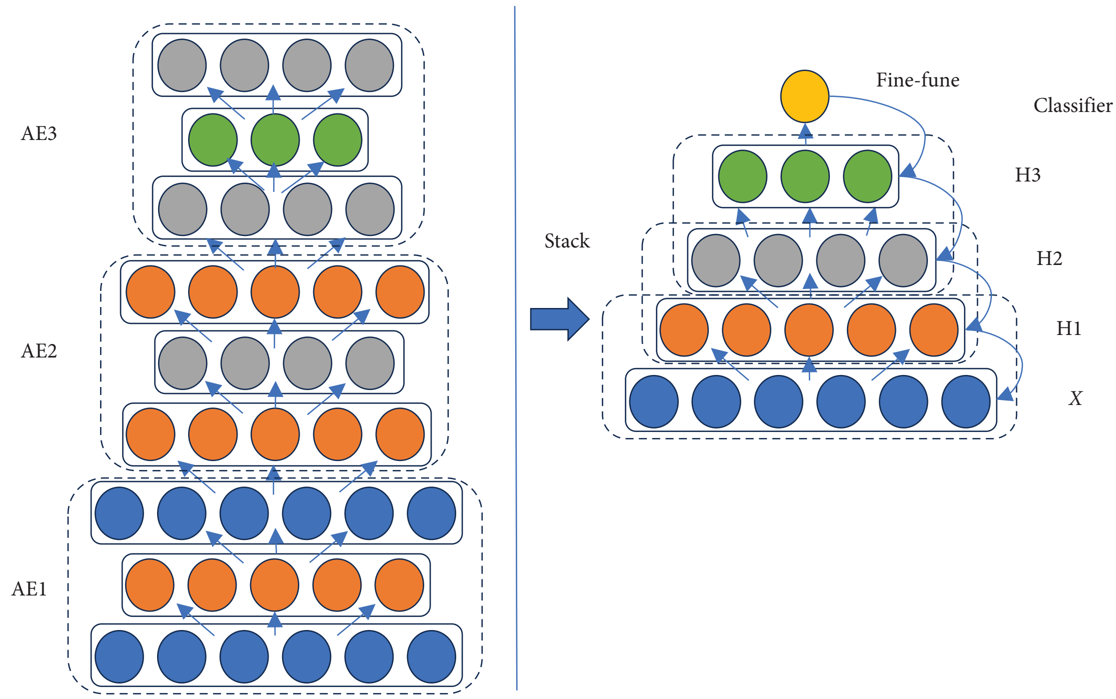


FIGURE 2: The framework of stacked autoencoders.

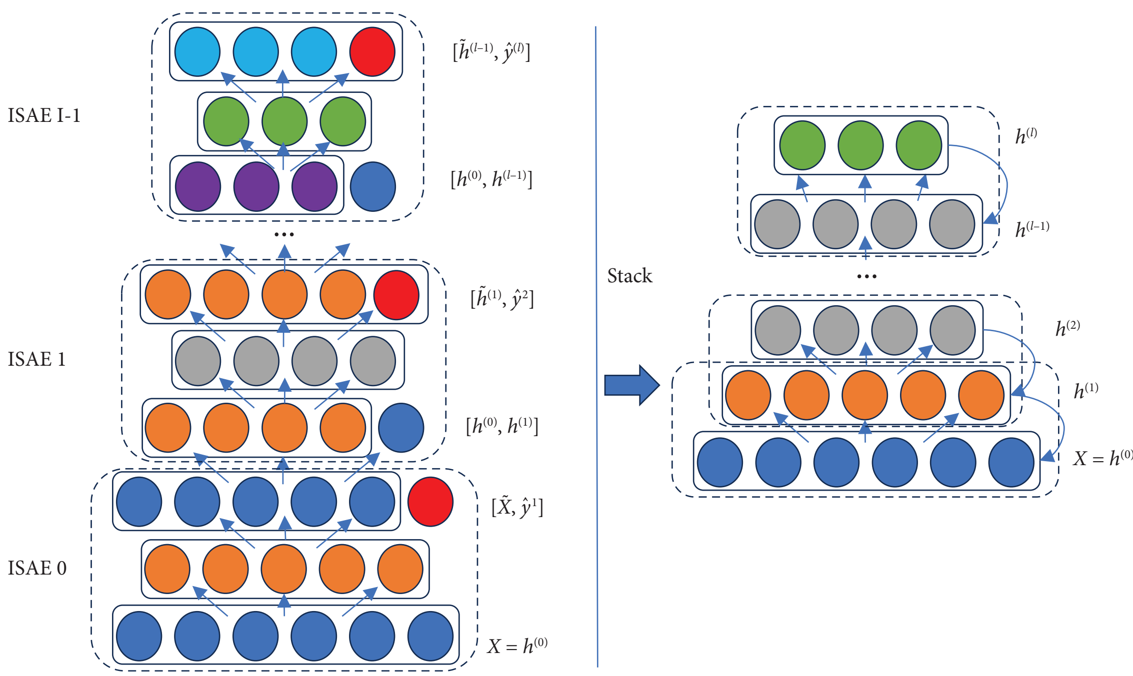


FIGURE 3: The framework of SISAE.

- Step 3: After all layers are pretrained, we use backpropagation over the entire SISAE to fine-tune all parameters using the labeled training data.

By integrating input enhancement and supervised learning, SISAE learns a latent space $H \in \mathbb{R}^{n \times k}$ that is specifically tailored for fraud detection. This representation serves as the feature input for the METADES stage described in Section 3.2.

3.2. Classifying the Finacnial Satements Using the SISAE-METADES Framework. After obtaining task-relevant deep features from the SISAE, the subsequent step is to concentrate on financial statements fraud identification. METADES is a dynamic ensemble framework that employs meta-features to assess the capability of base classifiers [15]. Specifically, the dynamic selection problem can be considered as another classification problem, known as the meta-problem. This meta-problem utilizes different criteria regarding the behavior of the base classifier in order to determine whether it is competent enough to classify a given sample X_j. In the original METADES framework, five meta-features are used to evaluate classifier competence. However, this limited set may not fully capture a classifier's ability to detect financial fraud, especially when dealing with high-dimensional and imbalanced data. In this study, we extend the meta-feature set by adding two additional criteria—local accuracy variance and decision boundary proximity—specifically designed to enhance fraud detection capability assessment. Moreover, traditional METADES computes meta-features from raw input data, which can contain noise and irrelevant information, potentially degrading competence estimation. To address this, we integrate SISAE-derived latent features into the METADES framework. The SISAE's noise-resistant, class-discriminative representations improve the robustness and reliability of the meta-feature space, leading to more accurate base classifier selection for each query instance. The resulting SISAE-METADES framework (Figure 4) combines supervised deep feature learning with DES, enabling precise classification of financial statements as fraudulent or non-fraudulent while adapting to the local characteristics of each sample.

The goal of this stage is to identify the most capable classifier to identify whether a financial report is fraudulent or not. The specific process includes selecting examples, determining meta-feature vectors, and training meta-classifiers to confirm whether there is fraud in financial reports.

3.2.1. The Sample Selection Phase. Initially, a set of data sets $D_{tr\lambda}$ need to be selected from the training set for meta-feature extraction. The selection criterion is that if the classifier pool has a low consensus on a training instance, then the instance is selected. Specific calculation process: Each financial sample instance $x_{j,\text{train}} \in D_{tr}$ is identified by the classifier pool $C = \{c_1, c_2, \dots, c_M\}$. Then, the consensus of the classification pool $H(x_{j,\text{train}}, C)$ is calculated, expressed as the difference in votes between the winning class and the second class. If $H(x_{j,\text{train}}, C) < h_C$ (needs to be defined in advance), then $x_{j,\text{train}}$ can be added to $D_{tr\lambda}$.

3.2.2. Meta-Feature Extraction. The main purpose of this process is to calculate the meta-feature vector v_{ij}, that is, the performance of each base classifier $c_i \in C$ in the competence region of $x_{j,\text{train}}$. The specific process is as follows.

First, we calculate the competence region of $x_{j,\text{train}\lambda}$. We first select K nearest neighbors to generate $\theta_j = \{x_1, x_2, \dots, x_K\}$ according to the KNN algorithm. Then, we generate the decision space based on the competence region, that is, the label $\overline{x}_{j,\text{train}\lambda} = \left\{\overline{x}_{j,\text{train}\lambda,1}, \overline{x}_{j,\text{train}\lambda,2}, \dots, \overline{x}_{j,\text{train}\lambda,M}\right\}$ of $x_{j,\text{train}\lambda}$ predicted by the base classifier $c_i \in C$. Then, we select the instances corresponding to the K_p most similar output profiles as the competence region based on the decision space: $\phi_j = \left\{x_1, x_2, \dots, x_{K_p}\right\}$. Based on the result of θ_j, ϕ_j , the meta-feature vector $v_{i,j}$ can be extracted. In the original METADES, includes five types of meta-features $v_{i,j}$. The introduction of each meta-feature f_i is as follows:

- f_1 (Neighbors' hard classification): this feature is a vector with K elements. For instance x_k , if the prediction is correct, the value of the k th is 1; otherwise, it is 0.
- f_2 (Posterior probability): The set contains K elements; each element c_i represents the posterior probability of $P(\omega_l|x_k)$, where ω_l is the sample label.
- f_3 (Overall local accuracy): The set contains one element, representing the accuracy of the base classifier c_i on the entire feature space capability region θ_j.
- f_4 (Output profiles classification): This set is similar to f_1 but is based on the decision space. Therefore, it contains K_p elements; each element represents the local accuracy of c_i on the k th instance x_k in ϕ_j.
- f_5 (Classifier's Confidence): This set represents the normalized vertical distance between the instance $x_{j,\text{train}\lambda}$, the training λ, and decision boundary of the classifier c_i.

  Based on the origin METADES, we add two new criteria to provide a holistic approach to improve the stability of fraud detection models, ensuring that they remain accurate, adaptive, and resilient in the face of changing fraud strategies and complex transaction data.
- f_6 (Probability index): This feature contains one element, which represents the difference between the label probabilities predicted by the base classifier model c_i and the actual labels ω_k.

$$f_6 = -\frac{1}{K}\sum_{k=1}^{K}\left[\omega_k \log(p_k) + (1-\omega_k)\log(1-p_k)\right]. \quad (5)$$

- f_7 (Ambiguity index): The difference value between scores of the class with the highest support and the second highest one for the financial statement. For example, a base classification gets a score of a sample for a 2-class classification: 0.7 and 0.3. Then, the ambiguity index is $f_7 = 0.7\text{-}0.3 = 0.4$.

These additional criteria provide a holistic approach to improving fraud detection model stability, ensuring it remains accurate, adaptable, and resilient in the face of evolving fraud tactics and complex transaction data.

After this process, the meta-vector $v_{ij} = \{f_1 \cup f_2 \cup f_3 \cup f_4 \cup f_5 \cup f_6 \cup f_7\}$ is obtained.

In addition, the local accuracy of each classifier c_i on each $x_{j,\text{train}\lambda}$ is used as the meta-label α_{ij} of the meta-classifier; that is, if c_i correctly predicts $x_{j,\text{train}\lambda}$, $\alpha_{ij} = 1$; otherwise, $\alpha_{ij} = 0$, indicates the competence ability of c_i. Then, α_{ij} and v_{ij} are stored in T_λ^* as a meta-training dataset.

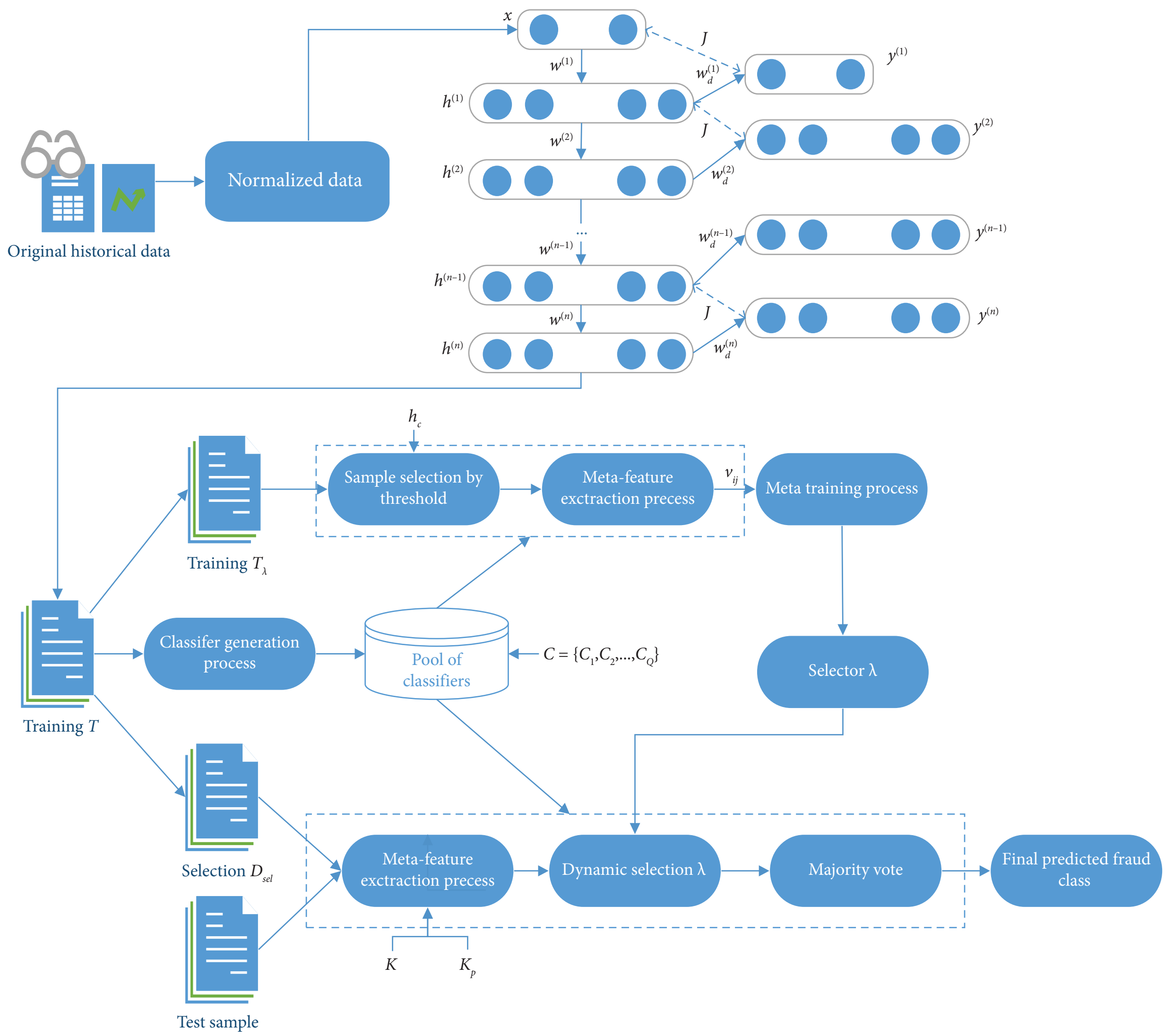


Figure 4: Framework of the proposed model.

3.2.3. Meta-Training Phase. Lastly, T_λ^* is used to train the meta-classifier λ. In this study, the multilayer perceptron (MLP) is chosen as the meta-classifier λ [15]. The number of nodes in the hidden layer is selected using the validation data. The configuration of 10 neurons is used in the hidden layer because the results do not improve beyond 10 neurons. The training process for λ is carried out using the Levenberg–Marquadt algorithm.

3.2.4. Generalization Phase. For the generalization process, the test data $x_{j,\text{test}}$ are input, and the corresponding meta-feature set T_λ^* can be obtained by extracting meta-features. The input of the meta-feature set into the meta-classifier λ can predict whether the base classifier $c_i \in C$ can correctly judge the fraud of the test data. Several base classifiers that are considered by λ to be able to correctly judge the test data $x_{j,\text{test}}$ are the base classifiers that are considered by MetaDES to have good performance. In this study, the majority voting rule is used due to its successful application in other DES algorithms. Finally, the prediction results of the selected base classifier set for the test samples $x_{j,\text{test}}$ are aggregated according to the predefined rules to obtain the final class ω_t.

3.3. Evaluation Methods. To assess the effectiveness of the proposed framework, several metrics are used.

3.3.1. Accuracy. This metric gauges the overall correctness of the model's predictions. It is determined by the ratio of correctly predicted instances to the total number of instances.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \quad (6)$$

where TP represents the number of true positives, TN denotes the number of true negatives, FP indicates the number of false positives, and FN signifies the number of false negatives.

3.3.2. Precision. This metric measures the proportion of true positive predictions out of all positive predictions. It is calculated as follows:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{7}$$

3.3.3. Recall. This metric assesses the proportion of actual positives that are correctly identified by the model. It is calculated as follows:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{8}$$

3.3.4. F1-Score. An alternative measure that strikes a compromise between precision and recall is the harmonic mean of these two factors. This metric is derived by employing the following formula:

$$\text{F1} - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{9}$$

3.3.5. AUC-ROC. The effectiveness of the model in distinguishing between the positive and negative classes is evaluated by this metric. The AUC-ROC represents the area under this curve, with values closer to 1 indicating better performance.

4. Experiments and Results

4.1. Experiments Datasets. According to CSMAR data, as of December 29, 2023, the finance industry has the largest market capitalization in the A-share market, exceeding 15 trillion yuan. Therefore, any fraud scandal financial industry could greatly impact the entire A-share market. For this reason, this paper focuses on listed companies in the financial sector, as classified by the CSRC 2012 industry classification. Companies labeled as *ST or ST, which face financial losses or special circumstances, are excluded from this study.

The sample period spans from January 1, 2005, to December 31, 2023. Fraud records for the samples are sourced from the CSMAR database. Given the timing of administrative penalty announcements by the CSRC, the year of fraud is uniformly defined: all reports within a year are considered fraudulent for that year [38]. If a specific year is not mentioned, the fraud year is assumed to be the year before the announcement. Additionally, the labeling of fraud instances is based on both the "violation or not" indicator from the CSMAR database and manual verification. This study examines 71 indicators, covering asset quality, profitability, cash flow, operating capacity, industry environment, and solvency [39]. Detailed definitions of these variables can be found in Table 1.

In this section, we commence by preserving the ratio of the two sample types and randomly allocate 80% of the total samples to the training set, which comprises 1213 samples and 152 fraud instances. Conversely, the remaining 20% of the samples, totaling 304, including 44 fraud samples, are designated for the test set.

The above experiments were performed in Python 3.9 on a Windows 10 system.

4.2. Experiment Setup. We choose four classical financial fraud recognition models: NN, SVM, extra tree (ET), and DT. When using DT as a single classifier, max_depth is set to 10 to preserve the classification effect. The ET model and other base classifiers used in the integrated methods are configured consistently with those employed in the SISAE-METADES framework, ensuring comparability across experiments.

Table 2 presents the key hyperparameters for each baseline classifier used during the preprocessing stage, along with the corresponding value ranges considered in the experiments.

To comprehensively evaluate the performance of the proposed SISAE-METADES framework, we design three categories of comparison models:(1) single hybrid models, which combine a dimensionality reduction method with a single base classifier; (2) DES methods, which apply DES algorithms directly without dimensionality reduction; (3) hybrid DES models, which integrate dimensionality reduction with DES.

The dimensionality reduction techniques considered include the SISAE, as used in our proposed method, and the conventional principal component analysis (PCA) baseline. The base classifiers and DES algorithms selected for comparison are NN, SVM, extra trees (ET), DT, and the well-known DES algorithms KNORA-E and KNORA-U. The SISAE hyperparameters and search ranges are summarized in Table 3. After tuning, the optimal hidden layer size was set to 20 nodes, resulting in a 20-dimensional feature space for the transformed fraud data.

The complete list of comparison models, along with their dimensionality reduction settings and classifier/DES configurations, is summarized in Table 4. This table provides a clear overview of how each model is constructed and ensures that the evaluation covers both single-model and ensemble-based paradigms under consistent experimental conditions.

4.3. Performance Comparison. Tables 5, 6, 7, and 8 report the average performance on accuracy, recall, F1-score, and AUC across 10 independent runs. Overall, SISAE-METADES achieves the highest scores across all metrics, with notable improvements in recall and AUC—two metrics that are particularly critical in fraud detection, where missing a fraudulent case is costlier than a false alarm.

In addition to the numerical comparisons, Figure 5 provides a visual summary of the results. The histogram clearly shows that SISAE-METADES consistently surpasses both base classifiers and advanced ensemble variants in all four-evaluation metrics. In particular, panels (a) and (d) illustrate its strong advantage in AUC and recall, while panels (b) and (c) confirm that F1-score and accuracy are also significantly enhanced. This visual evidence reinforces the robustness of the proposed method.

Table 1: Variable details.

Number	Variable name	Variable definition
1	ALR	Asset-liability ratio
2	EM	Equity multiplier
3	ER	Equity ratio
4	CFCER	Cash flow to capital expenditure ratio
5	CER	Capital expenditure ratio
6	BLR	Bank loan ratio
7	NRGL	Non-recurring gains and losses
8	EPS	Basic earnings per share
9	DEPS	Diluted earnings per share
10	TAR	Tangible asset ratio
11	IAR	Intangible asset ratio
12	FAR	Fixed asset ratio
13	REAR	Retained earnings to total assets ratio
14	NCLR	Non-current liability ratio
15	TAT	Total asset turnover
16	ART	Accounts receivable turnover
17	OC	Operating cycle
18	FAT	Fixed asset turnover
19	ROA	Return on assets
20	ROE	Return on equity
21	OPM	Operating profit margin
22	NOPM	Net operating profit margin
23	TAP	Total accrual profit
24	ETR	Effective tax rate
25	OI	Operating index
26	TCRR	Total cash recovery rate
27	NCOR	Net cash content of operating revenue
28	TAGR	Total asset growth rate
29	ROEG	Return on equity growth rate
30	NPG	Net profit growth rate
31	OPG	Operating profit growth rate
32	OEG	Owner's equity growth rate
33	ORG	Operating revenue growth rate
34	TQ	Tobin's Q
35	PE	Price-earnings ratio
36	MV	Market value
37	BMR	Book-to-market ratio
38	NE	Number of employees
39	BS	Board size
40	NE	Number of executives
41	NID	Number of independent directors
42	SBS	Supervisory board size
43	MC	Management compensation
44	TC3E	Total compensation of top three executives
45	SHSB	Number of shares held by supervisory board
46	SHBD	Number of shares held by board of directors
47	SHSB	Number of shares held by supervisory board
48	SHSM	Number of shares held by senior management
49	PID	Proportion of independent directors
50	MSR	Management shareholding ratio
51	AC	Analyst coverage
52	MC	Media coverage
53	TR	Turnover rate
54	OPY	Opening price of the year
55	CPY	Closing price of the year
56	ASTY	Number of shares traded annually
57	ATA	Annual trading amount
58	TMVY	Total market value of the year
59	ASRCDR	Annual stock return considering cash dividends reinvestment
60	CCE	Cash and cash equivalents

Table 1: Continued.

Number	Variable name	Variable definition
61	TA	Total assets (company size)
62	TE	Total equity
63	TL	Total liabilities
64	TOR	Total operating revenue
65	TOC	Total operating costs
66	OP	Operating profit
67	NP	Net profit
68	ECCE	Ending balance of cash and cash equivalents
69	BCCE	Beginning balance of cash and cash equivalents
70	NCFOA	Net cash flow from operating activities
71	CPEE	Cash paid to employees and for employees

Table 2: Configuration details of all base classifiers.

Model	Parameters	Value
Neural network (NN)	No. of hidden units	10
	Decay	0.5
SVM	Kernel function	Radial
	Gamma	1
Extra tree (ET)	*n*_estimators	100
	Criterion	'Gini'
Decision tree (DT)	Maximum depth	15

Table 3: The range of hyperparameters for stacked autoencoder model.

Hyperparameters	Search range
Number of layers in encoder and decoder	{2, 3, 4, 5}
Number of units in each layer	[1–512]
Bottleneck layer's units number	{10, 12, 14, 16, 18, 20, 22, 24, 26}
Loss function	{Mean squared error, mean absolute error, binary cross-entropy}

4.3.1. Comparison of the Proposed Model and the Base Classifier. Table 5 shows the average predicted scores of the proposed model and the base classifier, as well as the score differences between the models. Compared with the basic classifier, the SISAE-METADES model has better prediction ability, especially the accuracy, recall, and F1-score indicators to evaluate the classification performance. Under the AUC-ROC scoring standard, SISAE-METADES reached 0.7561; ET has the highest score of 0.6348 in the base classifier. Under the recall scoring standard, SISAE-METADES reaches 0.4321; NN has the highest score of 0.3215 in the base classifier. Under the F1-score scoring standard, ET has the highest score of 0.3563 in the base classifier, while the F1-score of SISAE-METADES is 0.3869. Under the accuracy scoring standard, the accuracy of both SISAE-METADES and the basic classifier is good, with the ET model reaching an accuracy of 0.7503 and SISAE-METADES reaching an accuracy of 0.8720. Compared with the base classifier, the AUC value of SISAE-METADES is improved by at least 0.1213, and the accuracy is improved by at least 0.1217. Recall value increased by at least 0.1106, and F1-score value increased by at least 0.0306. Moreover, this performance improvement is significant at the 1% significance level. In general, although the basic classifier has a good level of prediction accuracy in the model, it is difficult to obtain good results for the condition of high-dimensional features.

4.3.2. Comparison of the Proposed Model and the DES Methods. To further assess the effectiveness of SISAE-METADES, we compare it against four representative DES frameworks: the direct DES methods KNORA-E and KNORA-U, the standard METADES, and an improved METADES variant enriched with additional meta-features.

The results in Table 6 and Figure 5 indicate that SISAE-METADES exhibits the best overall performance in all recall metrics and accuracy, as well as F1-score, among the fraud prediction models for domestic listed companies. For instance, its recall reaches 0.4321, which is more than 0.0992 higher than KNORA-E (0.2934) and KNORA-U (0.3329), and 0.1208 higher than METADES (0.3113), and even 0.1011 higher than the improved METADES (0.3310). In terms of accuracy, SISAE-METADES reaches 0.8720, significantly higher than KNORA-U (0.8094) and METADES (0.8237). Similarly, its F1-score and accuracy also surpass those of all competing DES methods. In summary, these results demonstrate that SISAE-METADES not only outperforms the direct DES baseline but also shows significant improvements in advanced DES methods based on meta-learning. These findings confirms the importance of incorporating supervised deep representation learning into the DES process for handling high-dimensional and imbalanced financial fraud data.

Table 4: Experimental comparison models for SISAE-METADES evaluation.

Category	Dimensionality reduction	Base classifier/DES method	Model name
Single hybrid models	SISAE	NN	SISAE_NN
	SISAE	SVM	SISAE_SVM
	SISAE	ET	SISAE_ET
	SISAE	DT	SISAE_DT
	PCA	NN	PCA_NN
	PCA	SVM	PCA_SVM
	PCA	ET	PCA_ET
	PCA	DT	PCA_DT
DES methods	None	KNORA-E	KNORA-E
	None	KNORA-U	KNORA-U
	None	Origin METADES	METADES
	None	Improved METADES	Improved METADES
Hybrid DES models	SISAE	KNORA-E	SISAE_KNORA-E
	SISAE	KNORA-U	SISAE_KNORA-U
	PCA	KNORA-E	PCA_KNORA-E
	PCA	KNORA-U	PCA_KNORA-U

Table 5: Effect of the proposed model and single classifiers.

Model	Recall	Accuracy	AUC-ROC	F1-score
SISAE-METADES	**0.4321**	**0.8720**	**0.7561**	**0.3869**
NN	0.3215 (0.1106***)	0.7314 (0.1406***)	0.5898 (0.1663**)	0.3212 (0.0657***)
SVM	0.2711 (0.161***)	0.7450 (0.127***)	0.5811 (0.175***)	0.2283 (0.1586***)
ET	0.276 (0.1561***)	0.7503 (0.1217*)	0.6348 (0.1213***)	0.3563 (0.0306***)
DT	0.3041 (0.128***)	0.6727 (0.1993***)	0.5701 (0.186***)	0.2708 (0.1161***)

Note: The numbers in the table represent the average scores of the models; Bold indicates the highest score under a certain grading scale; ***, **, and * represent performance differences at 1%, 5%, and 10% significance levels in the Wilcoxon test, respectively.

Table 6: Effect of the proposed model and the DES methods.

Model	Recall	Accuracy	AUC-ROC	F1-score
SISAE -METADES	**0.4321**	**0.8720**	0.7561	**0.3869**
KNORA-E	0.2934 (0.1387***)	0.8232 (0.0488***)	0.7201 (0.036***)	0.2983 (0.0886***)
KNORA-U	0.3329 (0.0992***)	0.8094 (0.0626***)	0.7312 (0.0249***)	0.3123 (0.0746***)
METADES	0.3113 (0.1208***)	0.8237 (0.0483***)	**0.7875** (−0.0314**)	0.3615 (0.0254***)
Improved METADES	0.3310 (0.1011***)	0.8484 (0.0236***)	0.744 (0.0121*)	0.3654 (0.0215***)

Note: The numbers in the table represent the average scores of the models; bold indicates the highest score under a certain grading scale; ***, **, and * represent performance differences at 1%, 5%, and 10% significance levels in the Wilcoxon test, respectively.

4.3.3. Comparison of the Proposed Model and Single Hybrid Models. In order to better compare the ability of SISAE and PCA in extracting complex features of fraud data, the dimension reduction selection of PCA is the same as that of SISAE, that is, $d = 20$. Table 7 section compares the differences in prediction performance among two common types of dimension reduction (PCA and SISAE) and SISAE-METADES.

Firstly, in general, the use of dimensionality reduction can improve the prediction accuracy of the financial fraud identification model to some extent compared to the base model using the full set of features. Taking the DT base classifier as an example, under the recall criterion, SAE and PCA dimension reduction methods are used, which are both higher than the DT model under the full feature set. Secondly, taking SVM as an example, the SVM hybrid model using SAE scored higher under the criteria of accuracy, AUC-ROC, and F1. Finally, the results show that SISAE-METADES achieves higher prediction accuracy than the hybrid model using only dimensionality reduction.

4.3.4. Comparison of the Proposed Model and the Hybrid DES Models. We next compare SISAE-METADES with hybrid models that integrate dimensionality reduction and DES. Specifically, two variants employ PCA for dimensionality reduction (PCA_KNORA-E, PCA_KNORA-U), and two use SISAE-based features (SISAE_KNORA-E and SISAE_-KNORA-U).

As shown in Table 8 and Figure 5, the SISAE-based hybrids consistently outperform their PCA-based counterparts, confirming that supervised input-enhanced representation learning provides more discriminative features for dynamic selection. For instance, SISAE_KNORA-U achieves an AUC-ROC of 0.7239, which is higher than PCA_-KNORA-E (0.7021) and PCA_KNORA-U (0.7142). Similarly, in terms of recall, SISAE_KNORA-U reaches 0.4164,

Table 7: Effect of the proposed model and the hybrid models using dimension reduction.

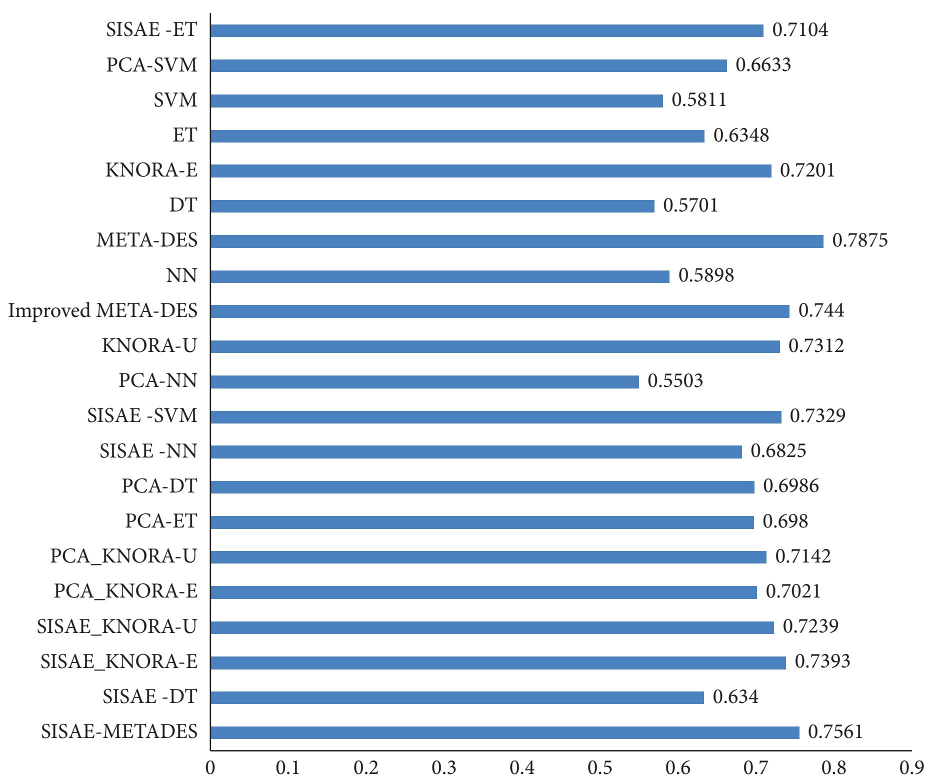
Model	Recall	Accuracy	AUC-ROC	F1-score
SISAE-METADES	**0.4321**	**0.8720**	**0.7561**	**0.3869**
SISAE-NN	0.3523 (0.0798***)	0.8239 (0.0481***)	0.6825 (0.0736***)	0.3435 (0.0434***)
SISAE-SVM	0.3421 (0.0900***)	0.8426 (0.0294***)	0.7329 (0.0232**)	0.3377 (0.0492***)
SISAE-ET	0.2101 (0.222***)	0.8251 (0.0469***)	0.7104 (0.0457***)	0.2761 (0.1108***)
SISAE-DT	0.4185 (0.0136***)	0.8097 (0.0623***)	0.634 (0.1221***)	0.3687 (0.0182*)
PCA-NN	0.342 (0.0901***)	0.7359 (0.1361***)	0.5503 (0.2058***)	0.249 (0.1379***)
PCA-SVM	0.2541 (0.178***)	0.8341 (0.0379***)	0.6633 (0.0928***)	0.2938 (0.0931***)
PCA-ET	0.3694 (0.0627***)	0.8209 (0.0511***)	0.698 (0.0581***)	0.3263 (0.0606***)
PCA-DT	0.3681 (0.064***)	0.8297 (0.0423***)	0.6986 (0.0575***)	0.3781 (0.0088***)

Note: The numbers in the table represent the average scores of the models; bold indicates the highest score under a certain grading scale; ***, **, and * represent performance differences at 1%, 5%, and 10% significance levels in the Wilcoxon test, respectively.

Table 8: Effect of the proposed model and the hybrid DES models.

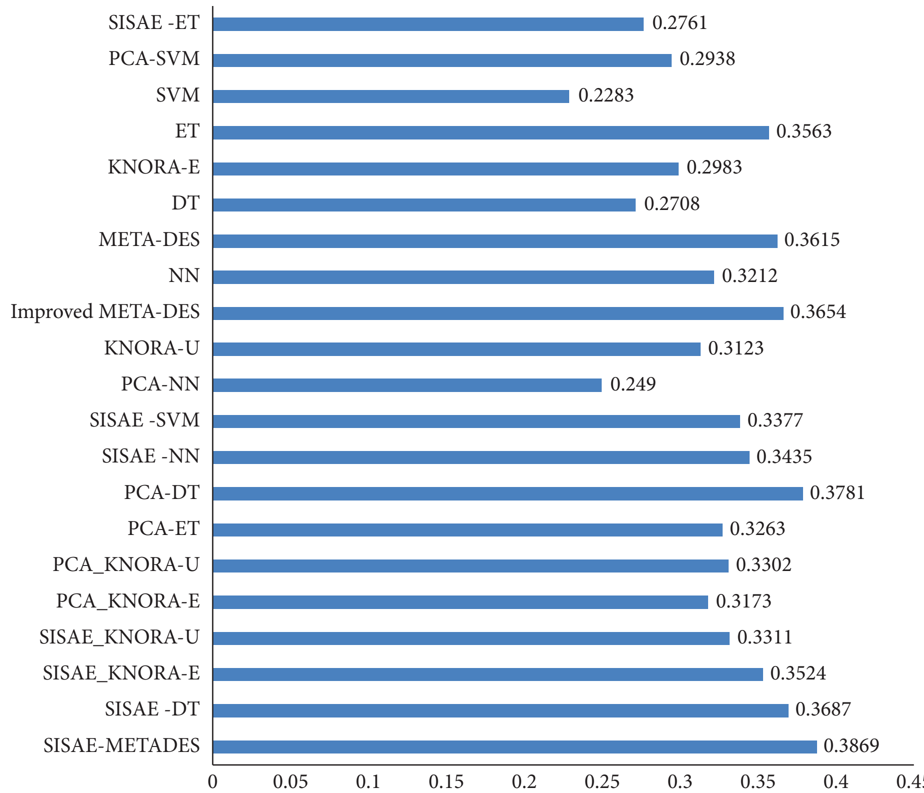
Model	Recall	Accuracy	AUC-ROC	F1-score
SISAE-METADES	**0.4321**	**0.8720**	**0.7561**	**0.3869**
SISAE_KNORA-E	0.4179 (0.0142*)	0.8321 (0.0399***)	0.7393 (0.0168***)	0.3524 (0.0345***)
SISAE _KNORA-U	0.4164 (0.0157**)	0.8309 (0.0411***)	0.7239 (0.0322***)	0.3311 (0.0558***)
PCA_KNORA-E	0.4133 (0.0188***)	0.8156 (0.0564***)	0.7021 (0.054***)	0.3173 (0.0696***)
PCA_KNORA-U	0.4127 (0.0194***)	0.8125 (0.0595***)	0.7142 (0.0419***)	0.3302 (0.0567***)

Note: The numbers in the table represent the average scores of the models; bold indicates the highest score under a certain grading scale; ***, **, and * represent performance differences at 1%, 5%, and 10% significance levels in the Wilcoxon test, respectively.

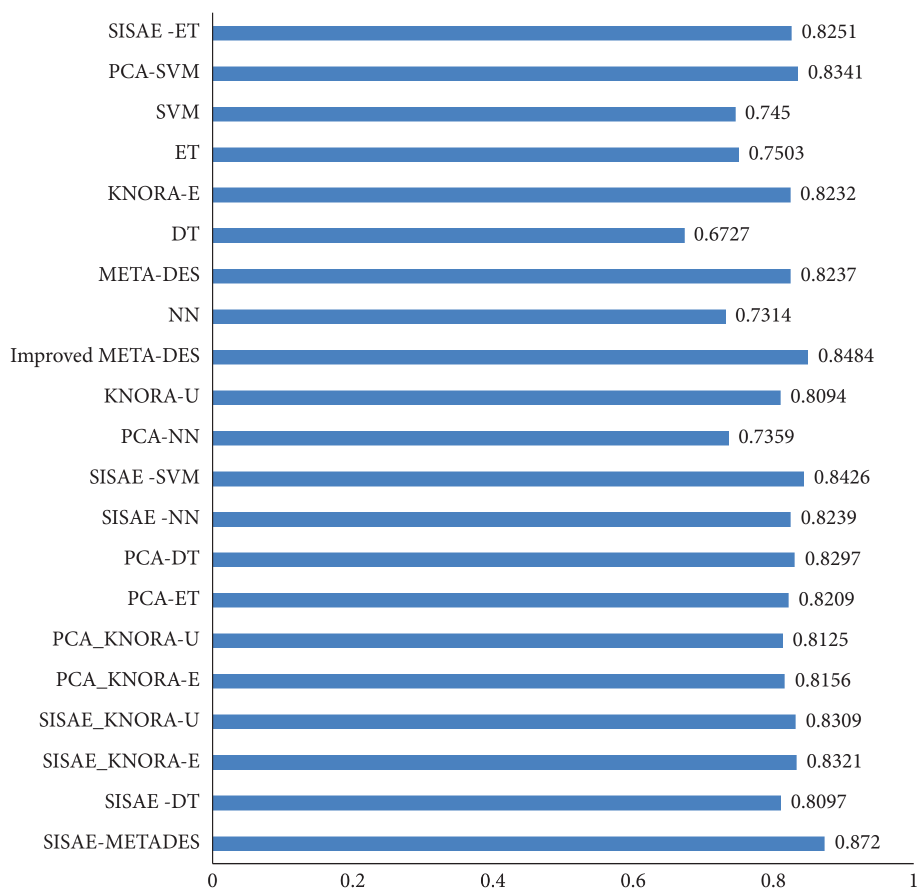


(a)

Figure 5: Continued.

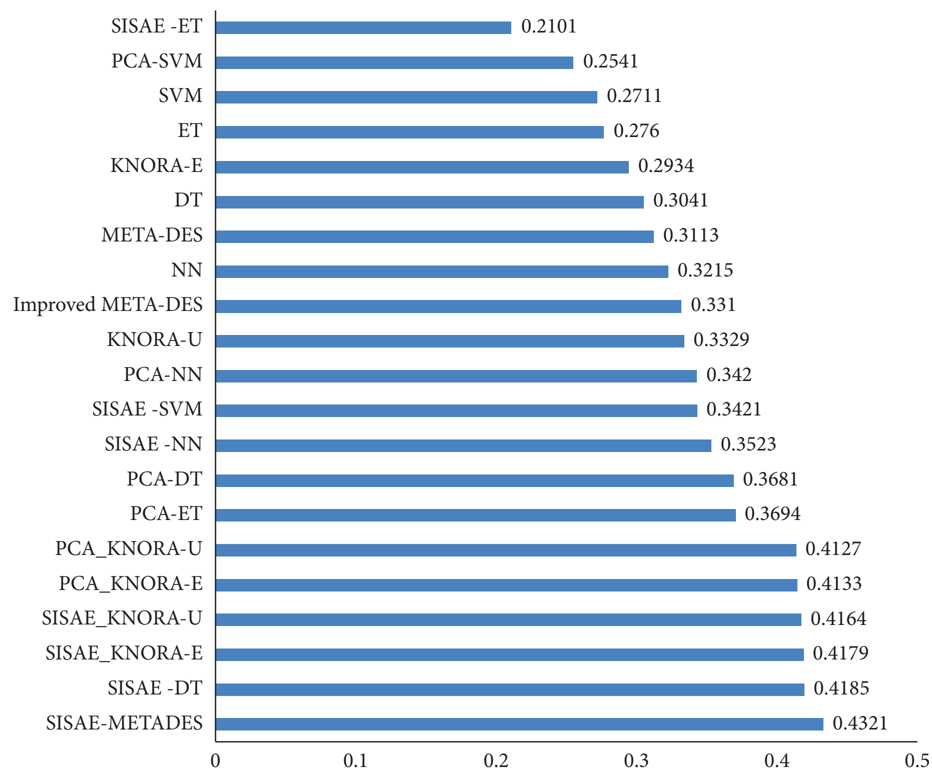


(b)



(c)

Figure 5: Continued.



(d)

Figure 5: Histogram of the mean scores for SA-METADES and the models using dimension reduction and DES. (a) AUC score of models. (b) F1-score of models. (c) Accuracy score of models. (d) Recall score of models.

Table 9: Results of ablation study on SISAE-METADES.

Model variant	Recall	Accuracy	AUC-ROC	F1-score
Improved SISAE-METADES	0.4321	0.8720	**0.7561**	**0.3869**
AE-METADES	0.4177 (0.0144***)	0.8265 (0.0455***)	0.7317 (0.0244***)	0.3546 (0.0323***)
SAE-METADES	0.4189 (0.0132***)	0.8583 (0.0137*)	0.7409 (0.0152***)	0.3604 (0.0265***)
SISAE-Voting	**0.4402** (−0.0081**)	0.8467 (0.0253***)	0.7381 (0.018***)	0.3591 (0.0278***)
Origin SISAE-METADES	0.4214 (0.0107***)	**0.8774** (−0.00534**)	0.7423 (0.0138***)	0.3687 (0.0182***)

Note: The numbers in the table represent the average scores of the models; bold indicates the highest score under a certain grading scale; ***, **, and * represent performance differences at 1%, 5%, and 10% significance levels in the Wilcoxon test, respectively.

which is also higher than PCA_KNORA-U (0.4127). These findings suggest that while SISAE features enhance traditional DES algorithms, the synergistic integration of SISAE with an enriched meta-feature design in SISAE-METADES leads to more reliable classifier competence estimation and superior fraud detection performance.

4.4. Ablation Study. To further validate the contribution of each component in the proposed SISAE-METADES framework, we conducted an ablation study by systematically removing or modifying key modules. The results are summarized in Table 9.

First, when replacing SISAE with a conventional SAE (AE-METADES), the performance dropped substantially, particularly with a 0.0455 reduction in accuracy and a 0.0323 decrease in AUC. This indicates that the supervised feature learning in SISAE plays a critical role in capturing class-discriminative representations that are essential for fraud detection. Second, when input enhancement was removed (SAE-METADES), the model failed to fully utilize the original input information, resulting in F1-score and AUC-ROC being 0.0265 and 0.0152 lower than those of the complete SAE-METADES model. This highlights the benefit of concatenating the original input with intermediate hidden layers, which helps preserve complementary information during feature extraction. Third, replacing the DES mechanism with a static majority voting scheme (SISAE + Voting) also degraded performance. Although the accuracy rate remained at a relatively high level of 0.4402, the accuracy and F1-score both decreased by 0.0253 and 0.0278 respectively, showing that dynamic selection is more effective than static combination in handling heterogeneous and imbalanced fraud detection tasks. Finally, in order to demonstrate the effectiveness of enriching meta-features, we further conduct an ablation study for the comparison between improved

SISAE-METADES and Origin SISAE-METADES implemental based on five meta-features the complete SISAE-METADES outperforms the original SISAE-METDES in terms of recall metric, AUC-ROC metrics and F1-score. This demonstrates that each component—supervised deep feature learning, enriched meta-feature construction, and DES—plays a synergistic role in improving classification robustness and operational efficiency.

5. Conclusions and Future Work

Financial reporting fraud has emerged as a critical challenge in modern financial markets, with far-reaching consequences for investors, stakeholders, and the stability of the financial system. Early and accurate detection of such fraud is essential to mitigate losses, preserve market confidence, and safeguard the integrity of corporate disclosures. However, the high dimensionality and dynamic nature of financial data make fraud identification particularly challenging, often exceeding the capability of traditional machine learning approaches.

To address this gap, we proposed the SISAE-METADES framework, which integrates a SISAE with an improved meta-learning–based DES (METADES) strategy. By jointly leveraging supervised deep representation learning and enriched meta-feature–driven ensemble selection, the framework provides a robust mechanism for capturing complex, nonlinear fraud patterns.

Experimental evaluations on financial statement data from China's A-share market demonstrate that SISAE-METADES consistently outperforms (1) basic classifiers (NN, SVM, ET, DT), (2) single hybrid models using dimensionality reduction, (3) direct DES methods, and (4) hybrid dimensionality-reduction–plus–DES models. In particular, SISAE-METADES achieves significant improvements in recall and AUC, metrics that are especially critical for fraud detection. These findings highlight the synergistic advantage of integrating SISAE with METADES and validate the model's effectiveness in high-dimensional, imbalanced financial fraud scenarios.

Despite its strong performance, this study has certain limitations that open avenues for future research. First, scalability should be examined by extending SISAE-METADES to other financial contexts such as credit card fraud, money laundering, and insider trading. Second, incorporating multimodal data sources (textual disclosures, market sentiment, and network structures of transactions) could further enhance detection accuracy. Third, future work may explore adaptive meta-learning strategies to improve competence estimation under evolving fraud patterns. Finally, explainability techniques should be developed to enhance model transparency, thereby supporting practical adoption by regulators and auditors.

Data Availability Statement

The data that support the fndings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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