

Detecting fraudulent financial statement under imbalanced data using neural network

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ABSTRACT

In this paper a novel approach for detecting fraudulent financial statements by employing a combination of neural networks and synthetic minority over-sampling technique (SMOTE) is introduced. This approach is designed to tackle the problem of imbalanced datasets prevalent in fraudulent cases, which if left unaddressed will hinder the model to accurately identify fraud. Three neural network models, each representing different fraud predictors as the input layer: 28 inputs raw financial data; 14 inputs financial ratios data; and 42 inputs combination both raw financial and financial ratios data are developed. Experimental validation using established research datasets is conducted to assess the performance of the proposed method. Performance metrics, namely area under the curve (AUC), precision, and sensitivity, are used for evaluation, comparing the proposed model against existing benchmark models found in literature. Results indicate that the proposed model achieves an AUC score of 70.6% and a precision score of 2.89%, in comparable to the existing models, with a sensitivity score of 83% outperforming all counterparts. The high sensitivity rate of the proposed model underscores its practical utility for auditors and regulators, as it minimizes the risk of false negatives, thereby enhancing confidence in fraud detection.

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1. INTRODUCTION

Financial statement misstatements may arise from either fraud or error, as stated by the International Federation of Accountants [1]. It is the auditor's responsibility to provide reasonable assurance that the financial statements are free from material misstatement. Misleading financial statements can incur significant costs, especially for investors, regulators, and society at large, as demonstrated in the Enron scandal—one of the most notable audit and accounting scandals in history and literature [2]–[4]. It began when Enron shocked the public by reporting a \$638 million loss. This case implicated its auditor, Arthur Andersen, which failed to detect the misstatement and engaged in document shredding related to Enron audits. This highlights the difficulty in detecting accounting misstatements.

Detecting accounting misstatements can be challenging due to several reasons such as the complexity of financial transactions, sophisticated fraud schemes, vast amount of data, and human error and bias. These challenges underscore the need for innovative approach such as data analytics and machine learning in auditing [3]–[5]. These technologies offer the potential to enhance audit effectiveness, improve risk assessment, and mitigate the impact of human limitations on audit quality.

Although data analytics and machine learning are expected to demonstrate a superior method, they are seldom to use on performing audit procedures. It is relatively unknown whether usage of data analytics and

machine learning are indeed transformational for the audit [6]. Various research has been conducted in searching of fraudulent financial statement detection, including utilization of supervised learning and unsupervised learning. Supervised learning is used including various models such as neural network [7]–[11], genetic algorithm [12], decision tree (DT) [8]–[10], [13], Bayesian network [8], [9], support vector machines (SVM) [8], [13]–[15], and logistic regression (LR) [16]. Unsupervised learning implementation use algorithm such as self-organizing map [17], [18] and k-means clustering [17]. One significant obstacle in machine learning is the imbalanced data challenge, where unequal class representation leads to inaccurate detection, with majority classes overshadowing minorities. Publicly available financial statements often exhibit severe imbalance due to the rarity of fraudulent instances compared to non-fraudulent ones. Therefore, it is crucial for models to address this imbalance.

This research aims to develop a model for predicting fraudulent financial statements from real public datasets and to tackle the imbalanced data issue. Three neural networks models with different types of inputs, namely raw financial data, financial ratios data, and a combination thereof, combined with synthetic minority over-sampling technique (SMOTE), are proposed in this study. The rest of this paper is organized as follows: in section 2, we outline previous efforts by researchers to detect fraudulence in financial statement, both using commonly balanced simulation data and imbalanced real data. Section 3 details the method we propose, utilizing a combination of neural networks and SMOTE to detect fraudulence in highly imbalanced real data. In section 4, the experimental results are presented and compared with those of previous researchers. Finally, in section 5, we conclude with a summary of our findings.

2. LITERATURE REVIEW

The existing literature has focused considerable attention on financial data as crucial indicators of fraud, encompassing both raw financial data and financial ratios. As fundamental components of financial statements, financial data have the potential to indicate fraud risk. For example, a liquidity ratio derived directly from raw financial data could serve as an effective measure of a company's financial pressure. This underscores the superiority of certain ratios over others [19], particularly those financial data points closely linked to the fraud triangle theory. By leveraging financial data, several approaches utilizing machine learning and data mining to detect fraudulent financial statement are found in the literature.

Green and Choi [7] demonstrated the potential of neural network applications in fraud investigation and utilized it as a detection tool, employing 172 samples, with 86 samples for both fraudulent and non-fraudulent cases. The model achieved an accuracy rate of 74%. Kotsiantis *et al.* [8] conducted experiments on DT, artificial neural network (ANNs), Bayesian networks, rule learners, nearest neighbors, and SVM. This study demonstrated that DT outperformed other models with 91.2% accuracy using a balanced dataset of 164 Greek companies listed on the Athens stock exchange, comprising 41 fraudulent and 123 non-fraudulent cases. In a similar works, Kirkos *et al.* [9] conducted experiments using DT, neural network, and Bayesian belief networks, revealing that Bayesian belief networks outperformed others with 90.3% accuracy using a balanced dataset of 76 Greek manufacturing companies, including 38 fraudulent and 38 non-fraudulent cases.

Cecchini *et al.* [14] using SVM, accurately identified 80% of fraudulent cases and 90.6% of non-fraudulent cases from a dataset comprising 6,427 non-fraudulent and 205 fraudulent samples. This study was considered a pioneering work in the field. Dechow *et al.* [16] presented an alternative method using LR with financial ratios to detect fraudulent financial statements, signaling the likelihood of misstatement. Perols [10], with a larger dataset of 15,934 non-fraudulent and 51 fraudulent cases, demonstrated that LR and SVM outperformed neural network, bagging, C.45, and stacking algorithm. These findings were consistent with those of Yao *et al.* [20], which showed that SVM had the highest accuracy among various classification methods.

Randhawa *et al.* [21] investigated the effectiveness of single and hybrid methods, employing under-sampling to detect credit card fraud. Their study revealed that combining AdaBoost and majority voting methods yielded the best results. Bao *et al.* [15] extended this research by using a large public dataset and compared the results of re-implementing the models proposed in [14], [16] with a new state-of-the-art model using RUSBoost. The proposed method outperformed the previous models with an area under curve (AUC) of 72.5% and sensitivity and precision of 4.88% and 4.48%, respectively. Hoang *et al.* [22] employed XGBoost and f-XGBoost on the dataset used in [15], resulting in AUC scores of 68.9% and 69.3%, and precision and sensitivity of 3.56%, 5%, and 3.36%, and 4.22%, respectively. Ashtiani and Raahemi [3] found that a single model outperformed both ensemble and hybrid approaches. They highlighted Temponeras *et al.* [23] approach of employing a deep dense multilayer perceptron, achieving an accuracy of 93.7% using a dataset of 164 Greek companies. Craja *et al.* [24] using a text mining approach to detect fraudulent financial statements from annual reports, demonstrated the effectiveness and preference for ANN, emphasizing their ability to capture complex relationships among variables. Inspired by the effectiveness of neural networks, this study proposes an approach combining neural networks and SMOTE to detect fraudulent financial statements in an imbalanced dataset.

3. METHOD

The detection model for fraudulent financial statement proposed in this study utilizes a combination of neural networks and SMOTE. Initially, a severely imbalanced public dataset containing real financial statements is acquired. Subsequently, the dataset undergoes preprocessing to address the imbalanced dataset using SMOTE, which generates synthetic samples for the minority class. The preprocessed data is then used for training and experimentation on the proposed network models. Finally, the results obtained from employing neural networks are compared to those achieved by the state-of-the-art algorithm proposed in previous literature. The overall process workflow is illustrated in Figure 1.

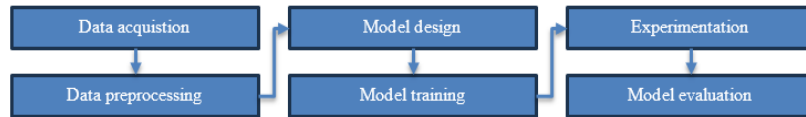


Figure 1. Proposed fraud detection workflow

3.1. Data and variables

The dataset is retrieved from previous research by Bao *et al.* [15], comprising 146,045 records collected from the COMPUSTAT database, covering all publicly listed U.S. firms from 1990 to 2014. It includes 42 features, consisting of 28 raw financial data derived from research by Cecchini *et al.* [14] and 14 financial ratios as researched by Dechow *et al.* [16]. Following the previous study, the training dataset spans from 1991 to the test year, with a two-year gap.

Serial fraud, defined as fraudulent cases spanning multiple years, is present in the dataset. The impact of serial fraud is that it can inflate the model's performance, as the same fraud case may be included in both the train and test data [15]. Therefore, to prevent overstated results and benchmark against previous literature, the dataset is preprocessed by recoding all serial fraud as non-fraudulent.

To address the severe imbalance between fraudulent and non-fraudulent cases in the dataset, we employ a minority oversampling technique called SMOTE [25]. This technique is necessary to address the challenge where the minority class is often neglected; for example, fraudulent cases represent only 0.67% of the population, which is the focus of our attention. SMOTE generates new synthetic data through an iterative process targeting each point in the minority class. It proves to be an effective method for addressing existing imbalance cases and improving classification performance [26].

3.2. Proposed artificial neural networks

This study experimented with the utilization of ANN, specifically feedforward networks, to detect fraudulent financial statements from a severely imbalanced dataset. The experiments involved three models or networks, each representing different fraud predictors as the input layer. The first network used 28 raw financial data as input layers derived from the fraud predictors of Cecchini *et al.* [14]. The second network used 14 financial ratios as input layers derived from the fraud predictors of Dechow *et al.* [16]. Lastly, the third network used a combined approach from Cecchini and Dechow as the input layer.

The overall architecture of the proposed networks is illustrated in Figure 2. The architecture of the three networks comprises an input layer followed by three hidden layers and an output layer. The input layer encompasses three different scenarios, representing different fraud predictors, which can be represented by input layers of 28, 14, and 42, respectively. Inspired in [23]–[25], the first and second hidden layers consist of fully connected layers with LeakyReLU (alpha of 0.05) as the activation function to address complex patterns and relationships of the fraud predictors and handle non-linearity issues. This is followed by L2 regularization with a coefficient of 0.005 to add a penalty term to the network to avoid overfitting issues [27]. The Adam optimizer is chosen for its capabilities of efficient computation, minimal memory requirements, and suitability for large datasets [28]. Additionally, a dropout layer is added with a rate of 0.7 to randomly drop out neurons in an attempt to prevent overfitting [29]. Finally, an output layer with a sigmoid function is added to perform binary classification tasks.

3.3. Performance evaluation

The performance of the proposed model is evaluated using three metrics: AUC, sensitivity, and precision. AUC is a metric used to evaluate the performance of binary classification [30]. It is employed to assess the accuracy of the proposed model due to the imbalance in the dataset, where the occurrence of fraudulent samples is not adequately captured in standard accuracy metrics [31]. Therefore, the AUC score provides a more representative measure of accuracy in this context compared to commonly used accuracy scores.

Following previous works [15], the measurement of sensitivity and precision is based on data from the top 1% of observations from the decision value. This choice is driven by practical considerations, as regulators may not be able to observe all companies predicted as fraudulent due to resource constraints. Additionally, this decision is influenced by the results of leading research by Cecchini *et al.* [14], which reported a high number of false positives in their SVM performance, correctly classifying 80% of fraud cases and 90.6% of non-fraud cases. Therefore, to mitigate the allocation of excessive resources toward many false positives, the focus is on the top 1% of observations.

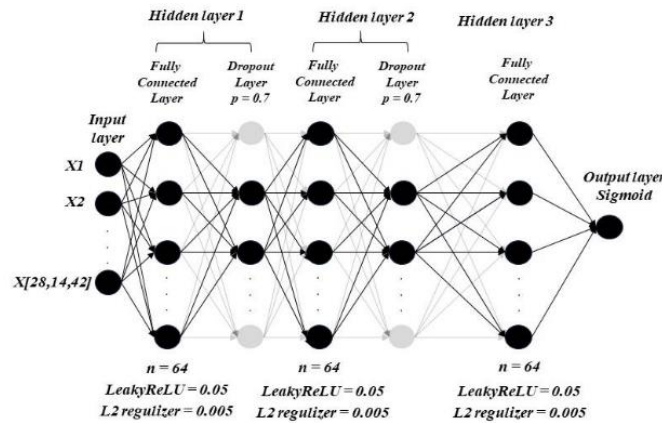


Figure 2. The architecture of the proposed networks

4. RESULTS AND DISCUSSION

This study proposed an approach for detecting fraudulent financial statements by combining neural networks and SMOTE. While earlier literature has explored and demonstrated the capability of various algorithms to detect fraudulent financial statements, there is still enhancement needed specifically in terms of accuracy. Therefore, developing a model with better accuracy is important, especially a model that can be relied upon for practical adoption.

Three networks with different fraud predictor as input layer are employed. The results obtained are summarized in Table 1. In the first network, employing raw financial data as fraud predictor, the proposed network scored an AUC score of 0.706, with a sensitivity of 50% and 1.39%. The second proposed network achieved AUC score of 0.693, sensitivity of 67%, and precision of 2.89%, by employing financial ratios as fraud predictor. Lastly, the third network employing both raw financial data and financial ratios as fraud predictor resulted in AUC of 0.672, followed by sensitivity of 83% and precision of 1.91%.

Table 1. Summary of comparison (test period 2003–2008)

Fraud predictor	AUC	Sensitivity (%)	Precision (%)
28 raw financial data	0.706	50	1.39
14 financial ratios	0.693	67	2.89
Both	0.672	83	1.91

As presented in Table 1, it is found that the proposed neural network can detect fraudulent financial statements, with raw financial data is the best fraud predictor measured by AUC score. These results demonstrated that combining both raw financial data and financial ratios as fraud predictor does not yield to a higher accuracy, measured by AUC score. From this experimentation, the highest precision is obtained through employing financial ratios as fraud predictor, whereas the highest sensitivity is obtained through employing both raw financial data and financial ratios as fraud predictor.

Table 2 provides results obtained from the proposed network for the test period of 2003–2008 in comparison with previous literature. These results demonstrate that the proposed network has comparable AUC score and precision in comparison with results obtained from previous literatures by employing algorithms with SVM, LR, RUSBoost, XGBoost, and f-XGBoost. In contrast, the proposed network demonstrates a superior sensitivity score, indicating that the model is able to identify fraud without producing a high number of false negatives, which could translate to undetected fraud. Hence, this demonstrates the model's assurance by ensuring reliability and practical utility or adoption. To show robustness of the proposed network, three alternative test periods are added. Consistent with previous study [15], [22], the additional test periods are

2003–2005, 2003–2011, and 2003–2014. The numerical figure of performance metrics for different additional test periods are presented in Tables 3 to 5.

Table 2. Summary of comparison with previous study (test period 2003–2008)

Fraud predictor	Model	AUC	Sensitivity (%)	Precision (%)	Reference
28 raw financial data	SVM	0.626	2.53	1.92	[15]
	Logistic	0.690	0.73	0.85	[15]
	RUSBoost	0.725	4.88	4.48	[15]
	XGBoost	0.689	3.56	3.36	[22]
	f-XGBoost	0.693	5.00	4.22	[22]
14 financial ratios	ANN	0.706	50	1.39	This study
	Logistic	0.672	3.99	2.63	[15]
	ANN	0.693	67	2.89	This study
Both	RUSBoost	0.696	3.19	2.54	[15]
	ANN	0.672	83	1.91	This study

Table 3. Summary of comparison with previous study (test period 2003–2005)

Fraud predictor	Model	AUC	Sensitivity (%)	Precision (%)	Reference
28 raw financial data	SVM	0.637	2.28	2.53	[15]
	Logistic	0.685	1.45	1.69	[15]
	RUSBoost	0.753	7.64	7.83	[15]
	f-XGBoost	0.691	6.59	6.71	[22]
	ANN	0.694	100	2.79	This study
14 financial ratios	Logistic	0.649	1.37	1.29	[15]
	ANN	0.667	67	2.53	This study
Both	ANN	0.656	100	2.52	This study

Table 4. Summary of comparison with previous study (test period 2003–2011)

Fraud predictor	Model	AUC	Sensitivity (%)	Precision (%)	Reference
28 raw financial data	SVM	0.647	3.07	1.98	[15]
	Logistic	0.702	1.87	1.19	[15]
	RUSBoost	0.710	4.40	3.60	[15]
	f-XGBoost	0.678	3.69	3.02	[22]
	ANN	0.720	56	1.34	This study
14 financial ratios	Logistic	0.672	3.49	2.23	[15]
	ANN	0.685	67	2.40	This study
Both	ANN	0.693	89	2.45	This study

Table 5. Summary of comparison with previous study (test period 2003–2014)

Fraud predictor	Model	AUC	Sensitivity (%)	Precision (%)	Reference
28 raw financial data	SVM	0.628	2.30	1.48	[15]
	Logistic	0.709	1.84	1.04	[15]
	RUSBoost	0.717	3.30	2.70	[15]
	f-XGBoost	0.678	2.77	2.26	[22]
	ANN	0.718	50	1.15	This study
14 financial ratios	Logistic	0.702	3.45	1.86	[15]
	ANN	0.694	58	1.99	This study
Both	ANN	0.686	75	2.02	This study

The results obtained are compared with previous literature and summarized in Figure 3. As shown in Figure 3, SVM model demonstrate fluctuations in the performance while both RUSBoost and XGBoost demonstrate a performance decline when the range of the set is extended. The results is accord to Hoang *et al.* [22], that the assumption of undetected fraud grows over time makes a longer test period less reliable. However, in contrast to SVM, RUSBoost, and XGBoost model, the proposed network, and logistic models show a slightly performance improvement for the extension of the test period. This demonstrates the robustness of both models and is expected to have a stable performance when tested with new unseen data.

Employing raw financial data as fraud predictor, the proposed network demonstrated the best AUC score in scenario of using full test set of 2003–2014 as shown in Table 5 by scoring AUC of 0.718 with precision of 1.15%, and sensitivity of 50%. Considering stability of AUC to demonstrate robustness, the proposed network score AUC of 0.694 and 0.720, in test period of 2003–2005 and 2003–2011 as shown in Tables 3 and 4, respectively. This shows that expanding dataset improves the performance of the proposed network. Then, in the next scenario using period of 2003–2014, the AUC score dropped to 0.718, slightly lower than previous scenario of 2003–2011. This indicates that while expanding dataset improves the performance,

there may be a diminishing return in a certain length of periods. Consistent with the results of Bao *et al.* [15], this study results demonstrated that when experimenting with the same model or networks, using 28 raw financial data that derived from [14] leads to a better result compared to using the other fraud predictors, which is 14 financial ratios derived from [16].

This study results shows that combining neural network and SMOTE can detect fraudulent financial statements in a severely imbalanced dataset using raw financial data, financial ratios, or both combined as the fraud predictor. While the proposed network demonstrated promising utility, it is important to acknowledge that the dataset used consists of historical data that coming from specific demographics and time periods. This may promote limitations on generalizability, hence require further calibration or updates to maintain its effectiveness in the current dynamic environment.

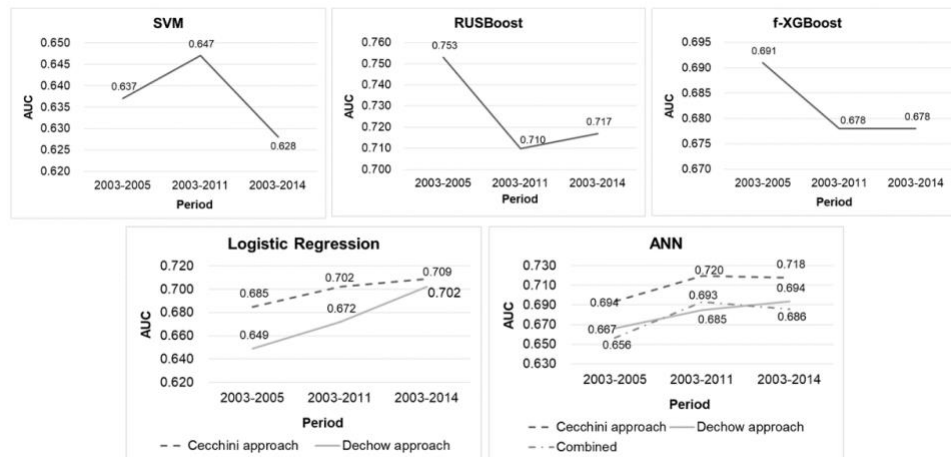


Figure 3. Summary of AUC scores over the additional test periods

5. CONCLUSION

This paper introduces a neural network designed to detect fraudulent financial statements within an imbalanced dataset, addressing the severe imbalance issue through the utilization of SMOTE. Our experiment results indicate that the model achieves detection capabilities, with an AUC score of 70.6%, a sensitivity rate of 83%, and a precision rate of 2.89%. This study contributes significantly by advocating for the integration of ANN in auditing practices, particularly during the initial audit phase, such as risk assessment procedures. The proposed model's high sensitivity rate underscores its superiority over similar models, offering practical utility for auditors and regulators by minimizing the risk of false negatives. However, limitations exist, including the reliance solely on numerical financial data extracted from financial statements. Future research avenues could explore the combination of non-financial data and the application of unsupervised learning to address mislabeling issues, potentially through the implementation of generative artificial intelligence to generate fraudulent data for training purposes or describing fraud characteristics.




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