Semiconductor Optoelectronics, *Vol. 42 No. 2 (2023), 985-999*
https://bdtgd.cn/

Semiconductor Optoelectronics ISSN: 1001-5868

A SURVEY AND ANALYSIS OF ACCOUNTING FRAUD IN PUBLICLY TRADED FIRMS BASED ON MACHINE LEARNING TECHNIQUES

Siddharth Nanda[1], Dr. Vinod Moreshwar Vaze[2]
[1]Research Scholar, Dept. of CSE, Shri JJT University, Jhunjhunu, Rajasthan, India,
siddnanda89@gmail.com
[2]Guide, Dept. of CSE, Shri JJT University, Jhunjhunu, Rajasthan, India,
vinod.vaze@gmail.com

Abstract
The fraudulent acquisition of financial resources has become an increasingly pressing issue for modern corporations and other organizations. In this research, we examine how Machine Learning (ML) can be used to spot signs of accounting fraud in publicly listed companies. We begin by doing a literature analysis on the topic of fraud detection using ML in the financial sector, where we discuss the possible benefits of approaches and the drawbacks of the former. We create prediction models to spot clear indications of accounting fraud by using a number of ML methods, including Support vector machine (SVM), Random Forests (RF), Logistic Regression (LR), and Decision Trees (DT). Precision, recall, F1-score, and accuracy are only a few of the many performance criteria used in assessing these models. The results after review show that the accuracy rates of 99.9 for Uchhana et al., Asha et al., Ileberi et al., (2021), and Badriyah et al., (2018) are all the same and that the recall rate of 100 is only shown by Ileberi et al., (2021). The best results for accounting fraud detection have been achieved by Illeberi et al., (2021) with a precision score of 99.93 and by Badriyah et al., (2018) with an F1-score of 99.6.

Keywords: *Financial Fraud, Machine Learning, Fraud Detection, Credit card fraud.*

1. Introduction

Financial fraud is the practice of obtaining financial gains by fraudulent and illegal methods [1-2]. Fraud may occur in a wide variety of financial contexts, including the business sector, insurance industry, the tax system, and the banking system. [3]. Money laundering, fraudulent financial transactions, and other forms of financial crime have all emerged as serious problems for businesses in recent years [4]. Large sums of money are lost daily due to fraud, despite many attempts to limit such activities, which negatively impact the economy and society [5]. Several fraud detection detections were introduced many years ago [6].

More studies are being undertaken to prevent losses caused by fraudulent activities; however, they are not effective because identifying fraud needs in-depth professional knowledge and is thus increasing the duty of external auditors [7-9]. Figure 1 depicts the many methods of fraud analysis. In addition, documented conflicts of interest have damaged the trust of audit companies. The majority of current practices are manual, which is not just inefficient but also costly, incorrect, and time-consuming [10-11]. As a consequence, the development of reliable automated methods has emerged as a critical problem in the analysis of financial statement fraud. Investors (for better-informed choices), audit firms (for client acceptance and regular audits), and government regulators (for more focused investigative efforts) all benefit greatly from the systems' improved detection capacity [12-13].

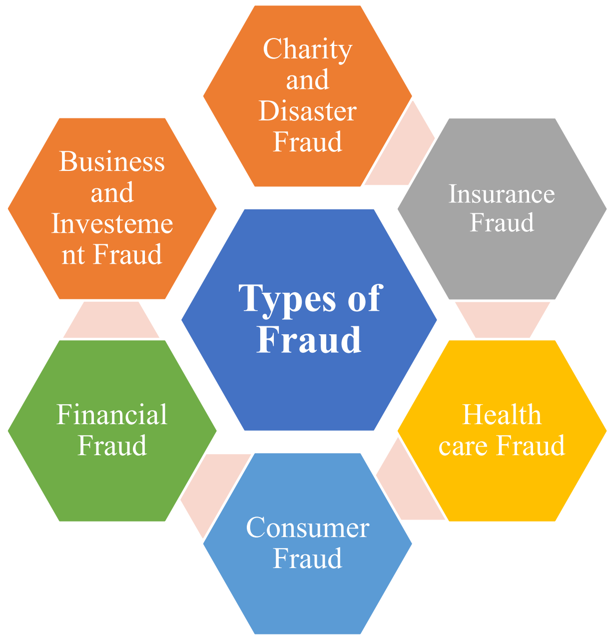

Figure 1: Types of fraud detection [14].

As a consequence, various Deep Learning (DL) and Machine Learning (ML) models are being used to detect fraud. To characterize some financial patterns that are hard to identify using conventional approaches and a large quantity of complex data, ML has the advantage over conventional rule systems. Various models, including Neural networks (NNs), Deep Neural Networks (DNNs), RFs, LR, SVMs, and others, are used to identify instances of financial fraud [15-18]. Credit card fraud detection methods are now well suited to online purchases because of the inherent differences between in-store and online credit card transactions.

1.1 Types of financial fraud

Here, we provide a quick overview of some of the most common varieties of financial fraud (Figure 2). Consumers, agents and brokers, insurance company personnel, healthcare professionals, and others could perpetrate insurance fraud at many stages in the insurance process [19].

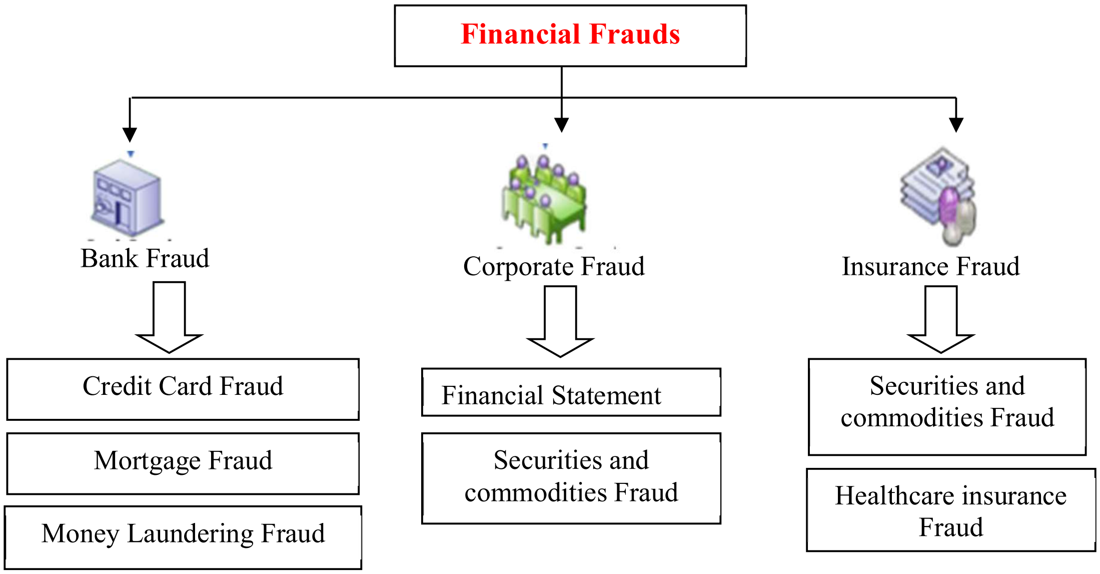

Figure 2: Common types of financial fraud.

- **Credit card Fraud**

A credit card is a compact, thin plastic or fiber card with the information (such as a photo or signature) of the individual authorized to charge goods and services to the account connected to the card. The financial harm that results from credit card theft has increased dramatically in recent years. Credit card fraud occurs when someone other than the cardholder makes illegal and undesired charges on their card [20]. Credit card fraud occurs when a person makes unauthorized purchases on another person's credit card while both the cardholder and the card issuer are completely unaware of the transaction [21]. As more advanced technologies become available, more and more business is being conducted online. Credit card use dominates these types of deals. These losses could be mitigated by taking preventative or detective measures against fraud. As the pace of technological development increases, new forms of fraud have emerged [22].

- **Financial Statements Fraud**

One of the most common forms of fraud, financial statement fraud consists of "material omissions or misrepresentations" in financial statements because of a "intentional failure to disclose financial data in accordance with widely accepted accounting rules [23]. Accounting fraud includes forging documents, documenting false transactions, omitting relevant events, and concealing information [24].

- **Security and Commodities Fraud**

Encouragement to make investments in a firm based on false information is a common kind of investment fraud. This can take many forms, including but not limited to currency exchange fraud, Ponzi schemes, pyramid schemes, and others [25].

- **Insurance fraud**

Insurance fraud is the assertion that incorrect funds were obtained from an insurance company or other underwriter, as opposed to the intended funds. Two notable industries that have experienced an increase in fraud are the motor and insurance industries [26]. Intentional asset misappropriation occurs when a person causes a false accident or loss of assets that leads to inflated medical and repair bills. Healthcare, agricultural, vehicle, and other insurance policies are not immune to insurance fraud. In the case of vehicle claims, fraudsters can submit a forgery with inflated medical expenses incurred as a result of a staged accident. Criminals committing insurance fraud in the healthcare industry could record inflated surgical costs by reporting fraudulent medical services. In addition, fraudsters can commit acts of crop insurance when they suffer disproportionately high losses as a result of fluctuations in agricultural prices or calamities [27].

1.2 Classification techniques for Fraud detection

Several different machine-learning algorithms are being used for this purpose. LR, NB, ANN, RF, and SVM are these methods [28].

- **Naïve Bayes (NB)**

NB is predicated on two assumptions. First off, every attribute in an entry that has to be categorized contributes equally to a decision. Second, all characteristics are statistically independent, which means that learning one attribute's value doesn't reveal anything about the values of any other attributes. Applying the Bayes rule for each class that the instance belongs to results in the classification of the instance [29].

- **Random Forest (RF)**

RF is an ML method that is built from a DT algorithm, and it is often used to address a wide variety of regression and classification issues. It aids in the accurate prediction of output from massive datasets [30]. In order to solve many difficult problems, the RF method combines several classifiers. The average mean of other trees' output could be predicted with the aid of the RF. As the number of trees grows, so does the accuracy of the prediction it makes. The random forest technique is useful for overcoming the shortcomings of the DT approach [31].

- **Logistic Regression**

LR is the model of choice for producing discrete outcomes from continuous inputs. LR models in mathematics provide 0 and 1 as their outputs, while in practice, the resulting functions produce decimals between 0 and 1. By using a threshold, the model turns all values below the threshold into 0 and all values above the threshold into 1. In the absence of a specified threshold in the function, values of probability more than 0.5 are converted to 1, while values less than 0.5 are converted to 0 [32].

- **Artificial Neural Network (ANN)**

An ANN is a set of computational operations meant to mimic the way the human brain processes and analyzes data. Artificial intelligence (AI) has this as its basis since it allows us to tackle an issue that would be impossible for people to handle on their own. With its efficient outcomes across a variety of challenges, the neural network has been validated for use in credit card fraud detection. Credit card fraud detection algorithms that use NNs are designed to function similarly to the human brain, which stores both recent experiences and knowledge gleaned from the past [33].

- **Support Vector Machine (SVM)**

SVMs depend primarily on structural risk reduction, as opposed to the empirical risk minimization emphasized by other NNs [34]. Vapnik first introduced this method in 1992 to fix bugs and address the issue of binary classification; nowadays, it has been expanded to include non-linear regression as well [35]. SVMs locate the hyperplane that maximizes the margin between any two classes by mapping the data to an existing extremely high dimensional space using a specific kernel function. The solution to SVM difficulties relies heavily on outlying data points. Such factors are referred to as support vectors [36].

2. Literature of Review

In this part, we will discuss the prior research that has been done on the topic of detecting fraud using machine learning.

Nguyen et al., (2022) [37] developed a novel ML model using the Extreme Gradient Boosting (XG-Boost) method and dubbed it fraud-XG-Boost. The suggested model not only incorporates the benefits of XG-Boost but can also detect signs of financial statement fraud. In this evaluation, they use a combination of NDCG@k and the Area Under the Receiver Operating Characteristics Curve (AUC). The experimental findings demonstrate that the novel approach outperforms three established methods (an LR model based on financial ratios, an SVM model, and a RUS-Boost model) by a slight margin.

Zhao et al., (2022) [38] developed LR, RF, XG-Boost, SVM, and DT single classification models, as well as three ensemble models, including a voting classifier, to forecast financial fraud records of listed businesses. From these findings, it can be inferred that the accuracy of the best single model is between 97% and 99%, whereas that of the best ensemble models is much over 99%. This demonstrates the superior predictive and detective abilities of the optimum ensemble model for corporate fraud. As a result, the optimal model is a hybrid consisting of both an LR model and an XG-Boost model.

Uchhana et al., (2021) [39] provided a comparison analysis of existing ML algorithms for detecting credit card fraud and offered new methods for doing effectively. In this experiment, ML algorithms are tested on a dataset created for the express purpose of detecting credit card fraud. SVM, NB, LR, K-Nearest Neighbors (KNN), and RF are the five algorithms used. RF provides the top-scoring result, followed by KNN.

Zeng et al., (2021) [40] suggested a layered design that could communicate with residual structure in a mutually beneficial manner. The authors present a new technique that is called Residual Layered Camouflage Resistant Graph Neural Networks (RLC-CARE-GNN). They use the recall, the AUC, and the F1-score to measure the efficacy of the suggested approach. The studies on the Yelp and Amazon datasets demonstrate that the recommended RLC-GNN method produces considerable gains under three metrics such as AUC, recall, and F1 score.

Asha et al., (2021) [41] estimated the incidence of fraud utilizing a number of different ML methods, including the SVM, the KNN, and the ANN methods. The results demonstrate that ANN is are more accurate predictor than SVM and KNN algorithms for credit card fraud detection. In addition, they differentiate between the successful supervised ML and deep learning strategies used to distinguish fraudulent from legitimate financial transactions.

Ileberi et al., (2021) [42] developed an ML-based system to identify credit card fraud using a real-world unbalanced dataset derived from European credit cardholders. The following ML techniques were used to assess this framework's efficacy: SVM, LR, RF, XGBoost, DT, and

Extra Tree (ET). The classification accuracy of these ML systems was improved by using the Adaptive Boosting (AdaBoost) method. The experimental results showed that the suggested approaches performed better when the AdaBoost was used.

Sailusha et al., (2020) [43] intended to concentrate their attention primarily on numerous ML techniques. Both the RF technique and the Ada-boost techniques are included in the progression. The precision, recall, accuracy, and F1-score are the criteria that are used to evaluate the outcomes of the two algorithms. Comparisons are made between the RF and Ada-boost algorithms. The RF that achieves the highest combined recall, precision, accuracy, and F1 score is chosen for use in the fraud detection procedure.

Badriyah et al., (2018) [44] use the Nearest Neighbour based Method (distance-based and density-based) and Statistics Methods (interquartile range) to identify the presence of fraud utilizing predictive modeling developed in the area of anomaly detection to detect the occurrence of fraud. The data set was a benchmarking dataset in the form of a minority report open dataset that was comprised of data pertaining to German car insurance. According to the findings of the experiments, the performance measurement that was achieved using the approach that was investigated in this paper is better in certain instances. The comparison of the relevant studies is shown in Table 1.

Table 1: Comparison of Literature of Review

Authors [Reference]	Techniques Used	Fraud Detection	Dataset Used	Outcomes
Nguyen et al., (2022) [37]	fraud-XG-Boost	Financial fraud	—	According to the experimental findings, the new model outperforms the three baseline models in terms of AUC (0.678), NDCG@k (0.030), Sensitivity (2.77), and accuracy (2.26%).
Zhao et al., (2022) [38]	LR, RF, XG-Boost, SVM, and DT	Financial fraud	Training and Testing datasets	The LR+XGBOOST model performed the best. It had a 98.523% accuracy rate, a 99.017% recall rate, and a 99.497% precision rate.
Uchhana et al., (2021) [39]	RF	Credit card	Credit card fraud detection dataset	Analyses comparing the suggested technique to others have shown that it has superior performance in terms of recall (0.90), F1-score (1.00), and Matthew's

				correlation coefficient (MCC) (0.89).
Zeng et al., (2021) [40]	RLC-CARE-GNN	Fraud Detection	Yelp dataset and Amazon dataset	On the Yelp dataset, they were able to increase recall by up to 5.66%, AUC by up to 7.72%, and the F1-score by up to 9.09%. It was able to enhance these same three indicators by as much as 3.66%, 4.27%, and 3.25% on the Amazon dataset.
Asha et al., (2021) [41]	ANN and SVM	Credit card	Train and Test dataset	The suggested approach (ANN) yields superior results in terms of the performance measures accuracy (0.992), precision (0.8115), and recall (0.7619).
Ileberi et al., (2021) [42]	SVM, LR, RF, XG-Boost, DT, and ET	Credit Card Fraud	European credit card fraud dataset	When compared to other models, the ET-AdaBoost is the best option because of its 99.99% accuracy, 99.99% recall, 99.99% precision, and 0.99 MCC.
Sailusha et al., (2020) [43]	RF	Credit card	Credit card fraud data	The Random Forest Algorithm outperforms the Adaboost algorithm in spotting credit card fraud, with an F1-score of 0.83, recall of 0.75, and accuracy of 1.
Badriyah et al., (2018) [44]	Nearest Neighbor and Interquartile Range	Auto Insurance	German car insurance dataset	Accuracy was increased from 94.4 to 99.9 percent with the distance-based technique, from 35.2 to 82.0 percent with the

				density-based method, and from 92.1% to 98.0% with the interquartile range method when the feature selection strategy was paired with a genetic algorithm.

3. Experimental Setup

Below are some metrics for performance that can be used to the proposed method. T_P (True positive): correct labels identifying the documents as valid.

- T_N (True negative): appropriately labelled fake documents that are fraudulent.
- F_N (False negative): Misclassification of valid documents as false records.
- F_P (False positive): false documents that have been mistakenly classified as genuine.

To evaluate the suggested technique and to make comparisons to others, the authors compute its accuracy, precision, recall, and f1-score [45]. The formulas for these are as follows:

$$Accuracy = \frac{T_P+T_N}{T_{Total\_Images}} \times 100 \tag{4}$$

$$Precission = \frac{T_P}{T_P+F_P} \tag{5}$$

$$Recall = \left(\frac{T_P}{T_P+F_N}\right) \tag{6}$$

$$F1-score = \frac{2\times Precision \times Recall}{Precision+Recal} \tag{7}$$

3.1 Comparison Analysis

In this section, we will define the comparison of all of the previous research that has been connected to fraud detection using an ML approach and has been provided by a variety of authors. Accuracy, recall, F1-score, and precision are the four aspects of previous research that are considered when evaluating it as a whole. The following Table 2 illustrates the comparison of the previously discussed literature.

Table 2: Comparison of Literature of Review

Author [Reference]	**Techniques Used**	**Accuracy**	**Recall**	**F1-score**	**Precision**
Nguyen et al., (2022) [37]	Fraud-XG-Boost	__	2.77	__	2.26%
Zhao et al., (2022) [38]	LR+XG-Boost	98.523	99.017	__	99.497%

Uchhana et al., (2021) [39]	RF	99.9	89	1.00	99.9
Zeng et al., (2021) [40]	RLC-CARE-GNN	__	91.83	89.18	__
Asha et al., (2021) [41]	ANN	99.9	76.19	__	81.15
Ileberi et al., (2021) [42]	ET	99.99	100	__	99.93
Sailusha et al., (2020) [43]	RF	99.8	75	83	94
Badriyah et al., (2018) [44]	Nearest Neighbor and Interquartile Range	99.9		99.6	

Figure 3 is a graph showing the recall parameter value supplied by a number of authors over many years. Ileberi et al., (2021) [42] exhibit the greatest recall value in this graph, which is 100, while Nquyen et al., (2022) [37] present the lowest recall value, which is 2.77.

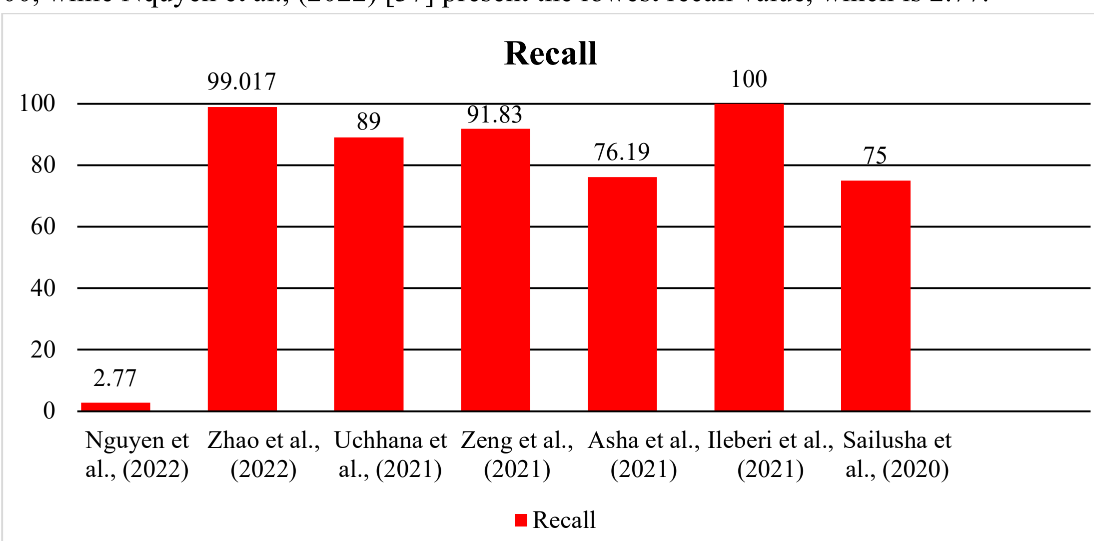

Figure 3: Graph of Recall parameter

Figure 4 presents a graph of the precision parameter value, the analysis of which was carried out using the literature that was shown before. The graph demonstrated here shows that Illeberi et al., (2021) [42] obtained the greatest result, which is 99.93, while Nguyen et al., (2022) [37] produced the lowest value, which is 2.26. The arrangement of all of the values, decreasing from highest to lowest:

Illeberi et al., (2021) > Zhao et al., (2022) > Uchhana et al., (2021) > Sailusha et al., (2020) > Asha et al., (2021) > Nguyen et al., (2022), all of which had values of 99.93 > 99.49 > 99.9 > 94 > 81.15 > 2.26.

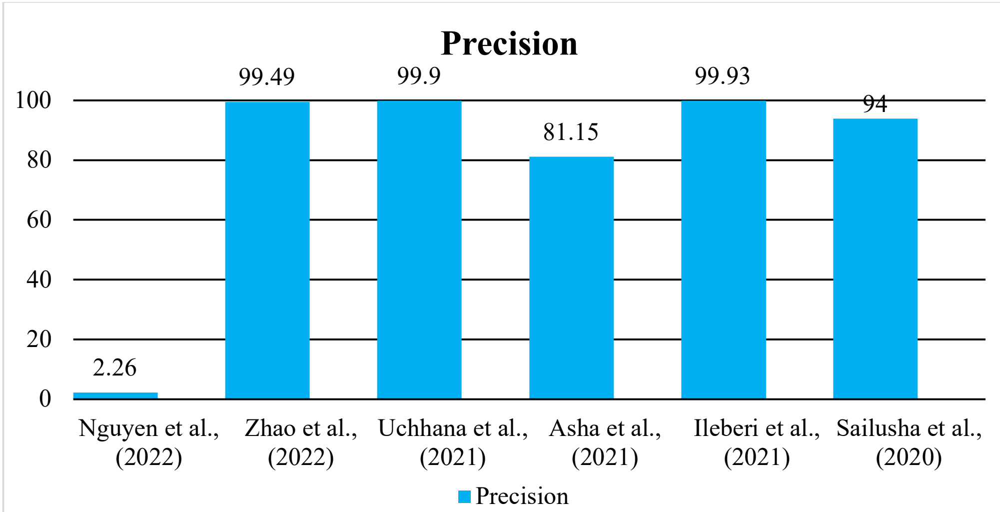

Figure 4: Graph of precision parameter

The curve illustrating the accuracy parameter is shown in Figure 5. This graph shows that four writers (Uchhana et al., Asha et al., Ileberi et al., (2021), Badriyah et al., (2018)) achieved the same level of accuracy, which is 99.9%. In addition, Sailusha et al., (2020) [43] have an accuracy that is 0.1 value points lower than the greatest accuracy, which is 99.8. In addition to this, Zhao et al., (2022) [38] achieve an accuracy of 98.52.

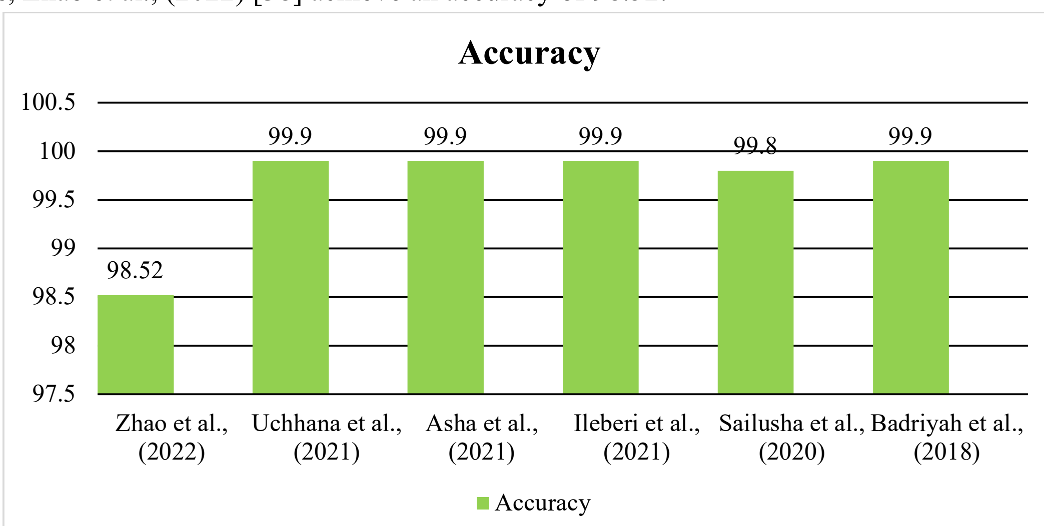

Figure 5: Graph of Accuracy parameter

Figure 6 presents a graph of the precision parameter value, the analysis of which was carried out using the literature that was shown before. The graph demonstrated here shows that Badriyah et al., (2018) [44] obtained the greatest result, which is 99.6, while Uchhana et al., (2021) [39] produced the lowest value, that is 1.

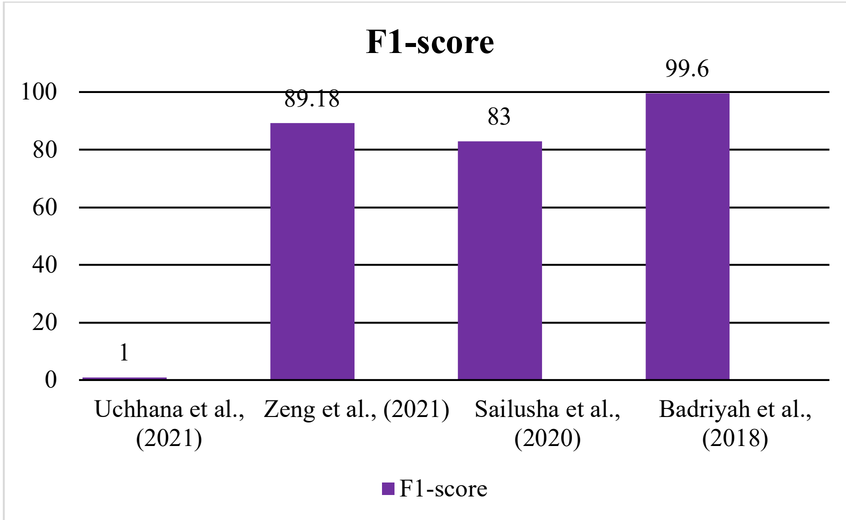

Figure 6: Graph of F1-score

4. Conclusion

The insurance, banking, tax, and corporate spheres are only a few examples of the many areas vulnerable to financial fraud. The prevalence of financial fraud in recent years has made it an important issue for many different types of organizations. However, despite these efforts, financial fraud continues to cost businesses and people huge sums of money every day. In this survey study, we look at how publicly traded firms can utilize machine learning to detect accounting fraud. We review the literature on financial fraud detection, with an emphasis on supervised classification and regression techniques, including SVM, NNs, and LR. These models are evaluated using a wide variety of performance metrics, including F1-score, recall, precision, and accuracy. Reviewing these studies, we find that Uchhana et al., Asha et al., Ileberi et al., and Badriyah et al., (2018) all report recall rates of 100% and that only Ileberi et al., (2021) report an accuracy rate of 99.9%. Illeberi et al. (2021) and Badriyah et al. (2018) have obtained the greatest results in accounting fraud detection, with a precision score of 99.93% and an F1 score of 99.6%, respectively.

Acknowledgment

The author would like to thank "Dr. Vinod Moreshwar Vaze" from "Shri JJT University" for his contributions to this review study. Their knowledge and contribution have been crucial to the development of this research. The author is also appreciative for the help and resources offered by the "Shri JJT University ". The author expresses his deepest gratitude to everyone who helped bring this study to completion.

Reference

1. Hilal, Waleed, S. Andrew Gadsden, and John Yawney. "Financial fraud: a review of anomaly detection techniques and recent advances." *Expert systems with applications* 193 (2022): 116429.
2. Ashtiani, Matin N., and Bijan Raahemi. "Intelligent fraud detection in financial statements using machine learning and data mining: a systematic literature review." *IEEE Access* 10 (2021): 72504-72525.

3. Albashrawi, Mousa. "Detecting financial fraud using data mining techniques: A decade review from 2004 to 2015." *Journal of Data Science* 14, no. 3 (2016): 553-569.
4. Choi, Dahee, and Kyungho Lee. "An artificial intelligence approach to financial fraud detection under IoT environment: A survey and implementation." *Security and Communication Networks* 2018 (2018).
5. Ryman-Tubb, Nick F., Paul Krause, and Wolfgang Garn. "How Artificial Intelligence and machine learning research impacts payment card fraud detection: A survey and industry benchmark." *Engineering Applications of Artificial Intelligence* 76 (2018): 130-157.
6. Ali, Abdulalem, Shukor Abd Razak, Siti Hajar Othman, Taiseer Abdalla Elfadil Eisa, Arafat Al-Dhaqm, Maged Nasser, Tusneem Elhassan, Hashim Elshafie, and Abdu Saif. "Financial fraud detection based on machine learning: a systematic literature review." *Applied Sciences* 12, no. 19 (2022): 9637.
7. Chaquet-Ulldemolins, Jacobo, Francisco-Javier Gimeno-Blanes, Santiago Moral-Rubio, Sergio Muñoz-Romero, and José-Luis Rojo-Álvarez. "On the black-box challenge for fraud detection using machine learning (ii): nonlinear analysis through interpretable autoencoders." *Applied Sciences* 12, no. 8 (2022): 3856.
8. Da'u, Aminu, and Naomie Salim. "Recommendation system based on deep learning methods: a systematic review and new directions." *Artificial Intelligence Review* 53, no. 4 (2020): 2709-2748.
9. Dyck, Alexander, Adair Morse, and Luigi Zingales. "Who blows the whistle on corporate fraud?" *The journal of finance* 65, no. 6 (2010): 2213-2253.
10. Al-Hashedi, Khaled Gubran, and Pritheega Magalingam. "Financial fraud detection applying data mining techniques: A comprehensive review from 2009 to 2019." *Computer Science Review* 40 (2021): 100402.
11. West, Jarrod, and Maumita Bhattacharya. "Intelligent financial fraud detection: a comprehensive review." *Computers & security* 57 (2016): 47-66.
12. Abbasi, Ahmed, Conan Albrecht, Anthony Vance, and James Hansen. "Metafraud: a meta-learning framework for detecting financial fraud." *Mis Quarterly* (2012): 1293-1327.
13. Hajek, Petr, and Roberto Henriques. "Mining corporate annual reports for intelligent detection of financial statement fraud–A comparative study of machine learning methods." *Knowledge-Based Systems* 128 (2017): 139-152.
14. Almutairi, Raghad, Abhishek Godavarthi, and Arthi Reddy Kotha. "Data Analysis for Fraud Detection in Finance." (2022).
15. Fu, Kang, Dawei Cheng, Yi Tu, and Liqing Zhang. "Credit card fraud detection using convolutional neural networks." In *Neural Information Processing: 23rd International Conference, ICONIP 2016, Kyoto, Japan, October 16–21, 2016, Proceedings, Part III 23*, pp. 483-490. Springer International Publishing, 2016.

16. Bhattacharyya, Siddhartha, Sanjeev Jha, Kurian Tharakunnel, and J. Christopher Westland. "Data mining for credit card fraud: A comparative study." *Decision support systems* 50, no. 3 (2011): 602-613.
17. Carneiro, Nuno, Gonçalo Figueira, and Miguel Costa. "A data mining-based system for credit-card fraud detection in e-tail." *Decision Support Systems* 95 (2017): 91-101.
18. Yin, Wenpeng, Katharina Kann, Mo Yu, and Hinrich Schütze. "Comparative study of CNN and RNN for natural language processing." *arXiv preprint arXiv:1702.01923* (2017).
19. Sadgali, Imane, Nawal Sael, and Faouzia Benabbou. "Performance of machine learning techniques in the detection of financial frauds." *Procedia computer science* 148 (2019): 45-54.
20. Yee, Ong Shu, Saravanan Sagadevan, and Nurul Hashimah Ahamed Hassain Malim. "Credit card fraud detection using machine learning as data mining technique." *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)* 10, no. 1-4 (2018): 23-27.
21. Maniraj, S. P., Aditya Saini, Shadab Ahmed, and Swarna Sarkar. "Credit card fraud detection using machine learning and data science." *International Journal of Engineering Research* 8, no. 9 (2019): 110-115.
22. Varun Kumar, K. S., V. G. Vijaya Kumar, A. Vijay Shankar, and K. Pratibha. "Credit card fraud detection using machine learning algorithms." *International Journal of Engineering Research & Technology (IJERT)* 9, no. 07 (2020): 5-8.
23. Gupta, Rajan, and Nasib Singh Gill. "Financial statement fraud detection using text mining." *International Journal of Advanced Computer Science and Applications* 3, no. 12 (2012).
24. Othman, Intan Waheedah. "Financial Statement Fraud: Challenges and Technology Deployment in Fraud Detection." *focus* 11, no. 4 (2021).
25. Ngai, Eric WT, Yong Hu, Yiu Hing Wong, Yijun Chen, and Xin Sun. "The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature." *Decision support systems* 50, no. 3 (2011): 559-569.
26. Urunkar, Abhijeet, Amruta Khot, Rashmi Bhat, and Nandinee Mudegol. "Fraud Detection and Analysis for Insurance Claim using Machine Learning." In *2022 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES)*, vol. 1, pp. 406-411. IEEE, 2022.
27. West, Jarrod, and Maumita Bhattacharya. "Intelligent financial fraud detection: a comprehensive review." *Computers & security* 57 (2016): 47-66.
28. Alfaiz, Noor Saleh, and Suliman Mohamed Fati. "Enhanced credit card fraud detection model using machine learning." *Electronics* 11, no. 4 (2022): 662.
29. Suryanarayana, S. Venkata, G. N. Balaji, and G. Venkateswara Rao. "Machine learning approaches for credit card fraud detection." *Int. J. Eng. Technol* 7, no. 2 (2018): 917-920.

30. Bin Sulaiman, Rejwan, Vitaly Schetinin, and Paul Sant. "Review of machine learning approach on credit card fraud detection." *Human-Centric Intelligent Systems* 2, no. 1-2 (2022): 55-68.

31. Darwish, Saad M. "An intelligent credit card fraud detection approach based on semantic fusion of two classifiers." *Soft Computing* 24, no. 2 (2020): 1243-1253.

32. Azhan, Mohammed, and Shazli Meraj. "Credit card fraud detection using machine learning and deep learning techniques." In *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)*, pp. 514-518. IEEE, 2020.

33. Sudha, C., and D. Akila. "Credit card fraud detection system based on operational & transaction features using svm and random forest classifiers." In *2021 2nd International Conference on Computation, Automation and Knowledge Management (ICCAKM)*, pp. 133-138. IEEE, 2021.

34. Li, Xurui, Wei Yu, Tianyu Luwang, Jianbin Zheng, Xuetao Qiu, Jintao Zhao, Lei Xia, and Yujiao Li. "Transaction fraud detection using gru-centered sandwich-structured model." In *2018 IEEE 22nd International Conference on Computer Supported Cooperative Work in Design ((CSCWD))*, pp. 467-472. IEEE, 2018.

35. Abakarim, Youness, Mohamed Lahby, and Abdelbaki Attioui. "An efficient real time model for credit card fraud detection based on deep learning." In *Proceedings of the 12th international conference on intelligent systems: theories and applications*, pp. 1-7. 2018.

36. Madhurya, M. J., H. L. Gururaj, B. C. Soundarya, K. P. Vidyashree, and A. B. Rajendra. "Exploratory analysis of credit card fraud detection using machine learning techniques." *Global Transitions Proceedings* 3, no. 1 (2022): 31-37.

37. Nguyen, Minh, Loan Nguyen Hoang To, and Hung Nguyen Viet. "A model for detecting accounting frauds by using machine learning." (2022).

38. Zhao, Zhihong, and Tongyuan Bai. "Financial Fraud Detection and Prediction in Listed Companies Using SMOTE and Machine Learning Algorithms." *Entropy* 24, no. 8 (2022): 1157.

39. Uchhana, N. R., R. Ranjan, S. Sharma, D. Agrawal, and A. Punde. "Literature Review of Different Machine Learning Algorithms for Credit Card Fraud Detection." *International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN* (2021): 2278-3075.

40. Zeng, Yufan, and Jiashan Tang. "Rlc-gnn: An improved deep architecture for spatial-based graph neural network with application to fraud detection." *Applied Sciences* 11, no. 12 (2021): 5656.

41. Asha, R. B., and Suresh Kumar KR. "Credit card fraud detection using artificial neural network." *Global Transitions Proceedings* 2, no. 1 (2021): 35-41.

42. Ileberi, Emmanuel, Yanxia Sun, and Zenghui Wang. "Performance evaluation of machine learning methods for credit card fraud detection using SMOTE and AdaBoost." *IEEE Access* 9 (2021): 165286-165294.

43. Sailusha, Ruttala, V. Gnaneswar, R. Ramesh, and G. Ramakoteswara Rao. "Credit card fraud detection using machine learning." In *2020 4th international conference on intelligent computing and control systems (ICICCS)*, pp. 1264-1270. IEEE, 2020.

44. Badriyah, Tessy, Lailul Rahmaniah, and Iwan Syarif. "Nearest neighbour and statistics method based for detecting fraud in auto insurance." In *2018 International Conference on Applied Engineering (ICAE)*, pp. 1-5. IEEE, 2018.

45. Roberts, A. (2014). Effects of alcohol consumption on MI risk—Evidence from INTERHEART. *Nature Reviews Cardiology*, *11*(8), 434-434.