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Machine Learning Algorithms and Auditor's Assessments of the Risks Material Misstatement: Evidence from the Restatement of Listed London Companies

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Abstract: The purpose of this study is to investigate the relationship between machine learning algorithms and auditors' assessments of the risks of material misstatement and restatement. Additionally, a focus on the effect of machine learning algorithms (SVM, Naïve Bayes, and K-means) on misstatement and restatement in London companies. The final sample of the study is 304 firm year observations. Which covers the listed firms on the London Stock Exchange and the period from 2018 to 2020. Especially, the firms that restated their financial statements -even just once- during the study period. The results showed a positive significant effect of machine learning techniques (K-means, Naïve Bayes, and SVM) on the intentional misstatements, which means that using machine learning techniques helps in determining the intentional misstatements. The results also showed a negative significant effect of the same techniques (K-means, Naïve Bayes, and SVM) on the restatements, which means that using machine learning techniques helps in avoiding the restatements.

Keywords: Machine Learning, Misstatement, Restatement, SVM, Naïve Bayes, K-means.

1. Introduction

The general objective of autonomous machine intelligence is artificial intelligence (AI), and the specific scientific method for reaching AI in this sense is machine learning [1]. All machine learning is included in artificial intelligence, but not all AI is machine learning. One example of artificially intelligent software that excludes machine learning is an algorithm.[2]

Machine learning is the process of analyzing data using algorithms, finding implicit patterns, and applying the patterns found to make predictions about the future. [3,1]

It has considerable interest from the social sciences and is undeniably enhancing data analysis. It offers methods for seeing trends in accounting studies and helps regulate control reporting practices [4]. Where [5] examine whether thematic disclosures in financial statements are incrementally informative in predicting intentional misreporting using machine learning techniques.

Accounting fraud is a global issue. It can directly impact numerous non-fraudulent companies. As well as the stakeholders of fraudulent companies like Enron and WorldCom, if it is not identified and stopped in a timely manner. Unfortunately, accounting fraud is hard to spot. Additionally, even if it is discovered, significant harm has typically already been done. As a result, authorities, auditors, and investors would greatly value good and efficient techniques for identifying corporate accounting fraud [6].

So, accounting errors and bankruptcies are critical events that can lead to huge investment losses [7].

1.1 Research Idea

Machine learning technology has developed to be used in the challenging field of auditing, which involves a lot of estimates and judgments [8]. Where the application of machine learning may have an impact on all phases of audit procedures from data preparation to decision-making [9]. Big Four companies make significant research investments in deep learning. For instance, KPMG works to analyze great amounts of structured and unstructured data pertaining to a

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company's financial information by using artificial intelligent. [10,3]

Big Four companies also have been utilizing machine learning to use big data in recent years in order to provide deeper insights and identify regions of higher risk, but the academic search of machine learning in audit is still in its early stages. The Researchers think that there are numerous opportunities for accounting professionals to learn how to effectively apply machine learning and other AI techniques [11,3].

The results demonstrate that machine learning ability to generate useful estimations of value-relevant data in some contexts. Where the study [12] A subset of artificial intelligence, specifically supervised learning, uses algorithms to create mathematical models using sample data, and it seeks to make a computer automatically understand patterns and trends from past data. Supervised learning assesses how well the constructed model predicts outcomes When using different data. The final objective of these algorithms is to identify the model that can produce the most precise and repeatable predictions on data that has never been seen before for a particular task [13].

1.2 Motivation of The Study

Although the firm management is in charge of the financial statements, auditors are required to plan and carry out audit processes that reduce audit risk. Prior studies have shown that stakeholders in the company hold the auditor partially accountable for major misstatements.[14]

The data also contain intricate patterns that machine learning algorithms are able to discern. These algorithms also choose the best variables to explain an outcome variable and the best combinations of variables to use when making accurate out-of-sample predictions. For better forecasting and decision-making, these algorithms are crucial for obtaining access to the vast and growing financial data sources. [4]

Where accounting errors and bankruptcies are critical events that can lead to huge investment losses [7] (Ding, 2019), The purpose of this study is to assess the impact of machine learning algorithms on intentional misstatement, restatement, and intentional misstatement on restatement in listed firms on the London Stock Exchange from 2018 to 2020. There were 73 restatements disclosed in 2018, which increased to 133 by 2020, for a total sample of 304.

The remainder of this study is divided into the following sections: The second portion is titled "Background and Literature Review." The third section contains the empirical study. The fourth section examines the conclusions, and the fifth section offers suggestions.

2. Background & Literature Review

2.1 Auditors' Assessments of Risks the Material Misstatement and Machine Learning

A difference between amount, classification, presentation, or disclosure of a reported financial statement item, and quantity, classification, presentation, or disclosure required for the item under the applicable financial reporting framework. Which is referred to as a misstatement. Material misstatements can be caused by different accounting policies chosen, incorrect implementation of accounting policies chosen, and inappropriate financial statement disclosure. [15,16].

Material misstatements related to inappropriate financial statement disclosure may involve: Financial statements that do not present disclosures in a way that is consistent with the usable financial reporting framework, removed disclosures that are required by this framework, or do not provide additional disclosures beyond this framework. All result in material misstatements. [15]

Archival financial research makes use of data streams that capture corporate characteristics, governance qualities, audit reports, market data, and accounting factors [4]. The inability of an auditor to gather adequate audit evidence may be due to management restraints, factors outside the auditors' control, or reasons related to the scope or duration of the audit [15].

In audit procedures, cutting-edge machine learning techniques can be included to help decision-making from planning through reporting. The study [3] suggests a paradigm for integrating deep learning into all phases of auditing. The framework illustrates how deep learning capabilities for structured data analysis interact into the audit environment.

So, these techniques can be used to automate a variety of audit procedures such as: substantive testing and tests of internal controls [13]. Machine learning implementation may have an effect on audit procedures at every stage from data preparation through decision-making.

By applying data collection criteria created with machine learning techniques in the early stages of audit work, auditors can obtain unbiased and more accurate information. Additionally, machine learning can interpret visual and natural language data to deliver integrated information from a variety of Big Data sources. [17]

In addition to comparing actual data to predictive data produced, auditors can utilize pattern recognition obtained from machine learning to find outliers and detect abnormalities. By analyzing auditing processes, machine learning can enhance auditing functionality and quality. [18 ,13]

As a result, machine learning algorithms can be developed for use by regulators, investors, and other stakeholders for more accurately assess and prediction of audit quality. Thereby better protecting the general public and ensuring the efficient operation of the capital market.[19]

Study of [19] illustrates that: 1) supervised learning algorithms can be used to predict audit quality accurately, especially when Random Forest is applied. 2) the variables that are most predictive of audit quality are the auditor's market share, the log of the client's total assets, the auditor's portfolio share, the log of audit fees, the auditor's size, and the auditor's brand name. 3) audit-related variables have higher predictive ability than financial variables.

Furthermore, decision-support tools for audit procedures have been developed using machine learning algorithms. Additionally, Deloitte introduces a novel method for doing investment evaluations and automating the audit of securities and investments, which is based on machine learning algorithms [20] .

Academic studies [12,18,6,21] have focused more explicitly on using machine learning to forecast frauds and audit quality. Application of machine learning to the specific requirements of auditors can enhance audit quality in practical, quick, precise, and extensive techniques by providing trusted audit evidence and supporting decision-making processes.

The study [14] analyze whether misstatement risk is estimated using machine learning algorithms and find that auditors' estimated misstatement risk is more likely to manifest when EMR rises. They also find evidence that EMR is significantly and positively correlated with audit fees and auditor switching for companies with Big N auditors but not for other companies.

According to [14], we can estimate the misstatement risk using the equation (1).

$$\begin{aligned} EMR = {} & \alpha_0+\alpha_1\ EMR_{it}\ (HIGH\_EMR,\ LOW\_EMR, CHG\_EMR)+\alpha_2\ BIG_{it}+\ \alpha_3\ EXPERT_{it} + \alpha_4\ CLIENT\_SIZE_{it} + \\ & \alpha_4 COMPLEXITY_{it} + \alpha_6 CURRENT\_\ ASSETS_{it} + \alpha_7 QUICK\_\ RATIO_{it} + \alpha_8 LEVERAGE_{it} + \alpha_9 ROI_{it} + \alpha_{10} LOSS_{it} + \\ & \alpha_{11} ZSCORE_{it} + \alpha_{12} BTM_{it} + \alpha_{13} AGE_{it} + \alpha_{14} BUSY_{it} + \alpha_{15} GCO_{it} + \alpha_{16} ICMW_{it} + \alpha_{17} TENURE_{it} + \alpha_{18} AUD\ HERF_{it} + \\ & \alpha_{19} OFFICE\_\ SIZE_{it} + \alpha_{20} MKT\ SHARE_{it} + \alpha_{21} CLIENT\ \_IMPORT_{it} + \alpha_{22} RETURN_{it} +\alpha_{23} VOLATILITY_{it} + \alpha_j SIC2\_\ FE \\ & + \alpha_j YEAR\_\ FE + £ \end{aligned} \tag{1}$$

In this context,[4] show the use of machine learning to identify and analyze trends in ongoing accounting fraud, by using a wide range of characteristics from accounting, capital markets, governance, and auditing databases to find material misstatements. This study demonstrates that accounting variables need to interact properly with audit and market variables in order to be effective at detecting misstatements.

[22] examine which greater likelihood of switching is linked to audit quality and usage of machine learning techniques to determine the possibility that a company switches auditors. The methodology is designed to help investors, audit companies, and regulators spot companies that are likely to change auditors in the future. According to this study, the companies that switch auditors more frequently have greater rates of misstatement and larger abnormal accruals.

The study of [13] aims to use Machine Learning in Accounting and Assurance. The researchers illustrate that machine learning is being applied in audit, analyzing business transactions, assessing risks. Additionally, the prediction of fraud, insolvency, substantial misstatements, and accounting estimates is done using machine learning. Machine learning is being applied in study and practice in accounting and auditing, which is raising questions about potential bias and ethical ramifications.

According to[23,24,15,22] , while deep neural networks, recurrent neural networks, deep learning are effective at computing input variables in order to create evaluation models, the Classification and Regression Tree (CART), which is a decision tree approach, is useful for identifying important variables. Therefore, material misstatement models may be evaluated using these algorithms, as follow:

2.1.1 Classification and Regression Tree (CART)

This technique is used to handle continuous and discrete non-parametric data. Based on the kind of data, it is divided into a classification tree and a regression tree, and it is employed whether the data are continuous or discrete, the binary technique iteratively divides the input data into two parts. Strong classification potential, straightforward classification regulation, handling of continuous and discrete variables separately, and only generating symmetric trees. [23,15].

2.1.2 Deep Neural Networks (DNN)

It is a fundamental deep learning technique created from artificial neural networks (ANN) with the objective of simulating the process of the human brain learning new knowledge. Thus, it is a fundamental deep learning technique. The deep neural network has more hidden layers than the artificial neural network. DNN with this structure is capable of dealing with more complex problems and processing large amounts of data.[15]

According to how it works, an artificial neural network inputs data to the output layer for processing by the neurons in the hidden layer, then outputs the results.

The equation displays the computation of the hidden layer (1). The activation function (AF) nonlinearly transforms the outputs processed by neurons after the data in the input layer have been multiplied by weights, added up with biases, and input into the subsequent layer until the desired results are obtained, and then the results are returned to adjust the weights.[15]

$$Y=AF\ (X1W1+X2W2+X2W3+\ldots+XNWN+bias) \quad (2)$$

2.1.3 Recurrent Neural Network

RNN is a common deep learning sequence model. It is used to handle ordered data and it is effective at capturing the time dependency of sequential data. As a result, it can predict time series data with a high degree of accuracy. At each time step, different forms of input can be evaluated while still preserving some crucial information thanks to the RNN structure. [25,26]

2.1.4 Random Forest

Which are machine learning algorithms that extract information from data and present it as decision trees. Nodes, branches, and leaves are the three components of a decision tree. The tree branches based on the input attributes, with each branch standing in for a choice. The tree's root node represents an input attribute. Each leaf node leads to a forecast of the goal value; a leaf is the tip of a branch. Decision trees can be used to solve problems involving regression and classification [24]. Overall, the more individual trees there are, the better the random forest's forecasting performance is.

2.1.5 Deep learning

Deep learning is an advanced machine learning technique that generates various leveled artificial neural networks to identify patterns in raw data and abstract data attributes [27]. The artificial neural network is composed of layers modeled after the structure and operation of the brain, which is made up of billions of interconnected biological neurons.

2.1.6 Support Vector Machine

The model makes best line or decision boundary in multidimensional space that divides different classes. So that new data points can be correctly categorized and predicted. The term "hyperplane" refers to this optimal decision boundary. SVM classifies datasets by generating the hyperplane in an iterative manner in order to reduce error and maximizes the marginal hyperplane. SVM chooses the extreme points in the creation of the hyperplane. These extraordinary situations are described by support vectors, and thus method is known as a support vector machine. The diagram below shows the classification of two distinct categories using a hyperplane: [5]

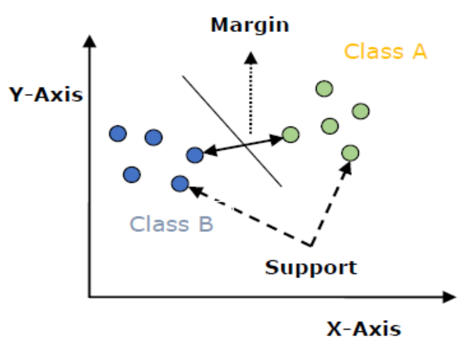

Fig. 1. SVM separating hyperplane in multidimensional space.

According to [28] study, SVM improves prediction models based on predefined dictionaries and models based on quantitative financial indicators when used to detect misreporting.

2.1.7 Naïve Bayes

Because it presumes that, the presence of one feature is unrelated to the occurrence of other features, the Naïve Bayes method is known as Naïve. Therefore, each trait works to identify a person on its own. Because it is based on the Bayes'

Theorem, it is also known as Bayes. One of the simple and quick ML techniques for classifying datasets is naive Bayes. In addition to binary classifications, it can also be utilized for multiclass classifications. It performs better in multi-class predictions than the other Algorithms. The " naïve " assumption that each pair of characteristics is independent underlies the Naïve Bayesian (NB) classifier, which is based on Bayes' theorem. NB theories state the following relationship: [19]

$$\mathrm{p}(y|x_{1,\dots}x_n) = \frac{p(y)p(x_{1,\dots.}x_n|y)}{p(x_{1,\dots}x_n)} \quad (3)$$

NB, assumption is:

$$\mathrm{p}(x_i|y, x_{1,\dots}x_{i-1}, x_{1i+1,\dots}x_n) = \mathrm{p}(x_i|y) \quad (4)$$

Thus, for all i the above relationship is simplified to: [19]

$$\mathrm{p}\ ((y|x_{1,\dots.}x_n) = \frac{p(y)\pi_{i=1}^{n}\ \mathrm{p}(x_i|y)}{p(x_{1,\dots,}x_n)} \quad (5)$$

2.1.8 K-Means Clustering Algorithm

The clustering difficulties are solved using the unsupervised learning process known as K-Means clustering. The unlabeled dataset is organized into various clusters using an iterative process, ensuring that each dataset only belongs to one group with the same attributes. Since the technique is centroid based, a centroid is assigned to each cluster. The algorithm's objective is to decrease the overall distances between each data point and its corresponding clusters as a result. It is explained in the diagram below: [29]

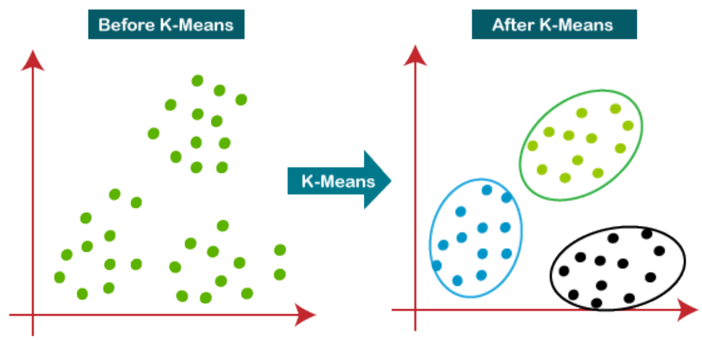

Fig. 2. K-means Clustering

2.1.9 Logit Regression

The most popular binary classification approach in the accounting studies is legit regression, which is accurate for predicting a dichotomous outcome when there are multiple independent variables. It is used to justify or anticipate errors in financial reporting, changes in auditors, and meeting earnings projections. [12]

The likelihood that earnings will grow the following year is estimated using the coefficient estimates provided by the model for the independent variables that are included in the model. As well as the realized values of the independent variables. An iterative procedure is used to estimate the logit regression coefficients and find the coefficients that minimize the difference between the projected likelihood of an increase in earnings and the actual probability of such increase (i.e., 1 for observations with increasing earnings, 0otherwise). As a result, this technique finds the value of b that maximizes Equation (1): [12,30]

$$Log\ p(y/\beta,x) = \sum_{i=1Yi}^{m} log\ \left(\frac{1}{1+exp\ (-x_i\ \ \beta}\right) + log\ \left(\frac{exp(-x_i\beta}{1+exp\ (-x_i\beta}\right) \quad (6)$$

Machine learning algorithms need to overcome a variety of challenges before they can be utilized by audit firms and regulators. Obtaining useful and relevant information from clients and outside sources may be difficult. Due to governmental and legal restrictions, auditors frequently do not have access to a significant amount of data from data repositories like Google or Facebook. Furthermore, auditors must follow particular ethical and client-friendly standards, which may restrict their access to the high-quality and substantial data needed to construct their training datasets.[31]

So, the three Common Audit Challenges according to [31,32,33] are as following:

First, Structured and Unstructured Data. An auditor may be required to differentiate between different types of data in order to support AI/ML techniques within firms from a risk management standpoint.

The procedures used to extract, transform, and load (ETL) the data so that it can be applied to business outcomes depend critically on the type of data being treated. Columns and rows that can be easily evaluated include how structured data is kept. It is currently the format that AI/ML approaches use the most. Unstructured data is information that is not saved in a logical order, like text. It could be more challenging to find and analyses data. Humans are typically better at comprehending unstructured data than AI/ML algorithms. [31,32,33]

The challenges of that data must be understood from the perspective of an auditor. All risks related to their use in Artificial intelligence and machine learning applications must be resolved. The majority of concerns are comparable for structured and unstructured data including survivor bias, expert bias, and data integrity. [32,33]

Second, Citizen Developers. Like any project, working on data analytics initiatives has depended on whether the information technology (IT) team had the resources and technical know-how. Projects are usually prioritized by organizations due to scarce resources and skilled employees. Making sure that data access is restricted to only authorized employees of the company is one of the most difficult components of the citizen improvement framework. [31]

Third, Data Bias. Which is a widespread issue. It is a disruption to the real data that causes partial notions to be embedded within it. Bias can also arise as a result of how data is interpreted. Machine learning makes decisions or predicts the next move using some form of historical data. Data Bias must be considered for machine learning applications because it can reduce data accuracy.

As data declines, it can reach a point where it misrepresents itself and no longer reflects population data. This can lead to incorrect decisions. When it related to machine learning techniques, Data Bias comes in many forms. To use machine learning approaches for risk management, the auditor must be aware of certain types of Data Bias. To make sure that the data is appropriately represented, these kinds of biases must also be taken into consideration while auditing machine learning techniques.

2.2 Restatements and Machine Learning

Restatements have been regarded as a reliable indicator of both reporting and audit quality for a long time [34]. It demonstrates both the inability of management to provide trustworthy financial statements and the incapacity of an auditor to find or disclose a financial inaccuracy. According to some, restatements should be categorized depending on management purpose because these errors reflect management's integrity and the auditor's knowledge or independence differently. Some others believe that restatements should be categorized according to management purpose, because these errors reflect on the competence or independence of the auditor in addition to management's moral character.

According to [7], Most balance sheet and income statement components are dependent on managerial estimations. These estimations are affected by managerial manipulation and objective estimation errors, which reduces the accuracy and value of financial reports. The study's findings demonstrate that machine learning may greatly improve the estimates. According to the research, machine learning techniques can help managers and auditors improve accounting estimations, raising the value of financial information to investors.

[35] concluded that, as compared to manual classification, machine learning is more consistent, repeatable, and scalable. Restatement disclosures and a supervised machine learning approach are used to classify restatements, leveraging information about both intentional misstatement and unintentional error in restatement announcements.

A machine learning classifier can classify restatements that do not explicitly disclose management intent, such as those coded as "GAAP violations" in the Audit Analytics database. [36]

Researchers currently use net income, market reaction, and other measures of restatement seriousness, but these do not always capture management intent. The majority of restatements, for example, cannot be classified based on market reaction. Similarly, partitioning on net income misses over one-third of recent restatements that have no effect on income and misclassifies restatements when managers intentionally manage earnings down rather than up. Restatement classification is less time-consuming, less resource-intensive, and less error-prone than manual classification once a classification algorithm is developed. [37,35]

The restatement classification approach that developed by machine learning in this study contributes in six ways. First, this approach directs the subjectivity associated with human coding to the coding of a comparatively little training set that provides advantages. Such as: reducing the human classification error, the time and effort required to classify a big number of restatements once the algorithm is developed.[35]

Second, this automated method classifies all restatements as either correcting intentional misstatement or correcting unintentional error. Third, the Naïve Bayes algorithm classifies restatements as reliably as other automated methods commonly used to partition restatements in accounting and audit research [35] .

Fourth, the method developed by combining the use of textual features in restatement disclosures with external information. Fifth, that evaluation provides comparative data on the performance of these algorithms in classifying restatements. Sixth, advanced programming skills may not be required to develop, validate, or select classifiers given the availability of machine learning tools [35].

There are numerous machine learning algorithms, and selecting a classification algorithm is an important step in restatement classification [38]. The sample size and preprocessing requirements of algorithms differ, as do the computational cost and speed, classification accuracy, and interpretability the ease with which humans can understand the models and results. [39,38]

Naïve Bayes and five other algorithms (Support Vector Machine, Decision Tree, Gradient Boosted Decision Trees, Logistic Regression, and Deep Learning Neural Network) classifiers are also reportedly used by financial institutions and insurance companies to detect fraud and are frequently used in accounting and audit research. [40,41,35]

According to [19], A key component of machine learning is supervised learning, in which learn algorithms from examples that are already accessible or from prior experience with known positive or negative "labels" and then predict future occurrences. A supervised learning algorithm, for example, can learn from existing examples how to distinguish a fraudulent transaction from a non-fraudulent one and then predict whether the next transaction is fraudulent or not. Artificial Neural Networks (ANN), Decision Trees (DT), Naïve Bayes (NB), Regressions, and Support Vector Machines are examples of supervised learning algorithms (SVM).[19]

3. Empirical study

3.1 Sample Selection:

There were 73 restatements disclosed in 2018. The number then increased to 133 by 2020. However, over the previous two years, there has been an 82% increase in restatements. The 73 restatements in 2018 only represented 4.1% of the corporations who published annual reports, though. At 5.6% in 2019 and 7.6% in 2020, this increased.

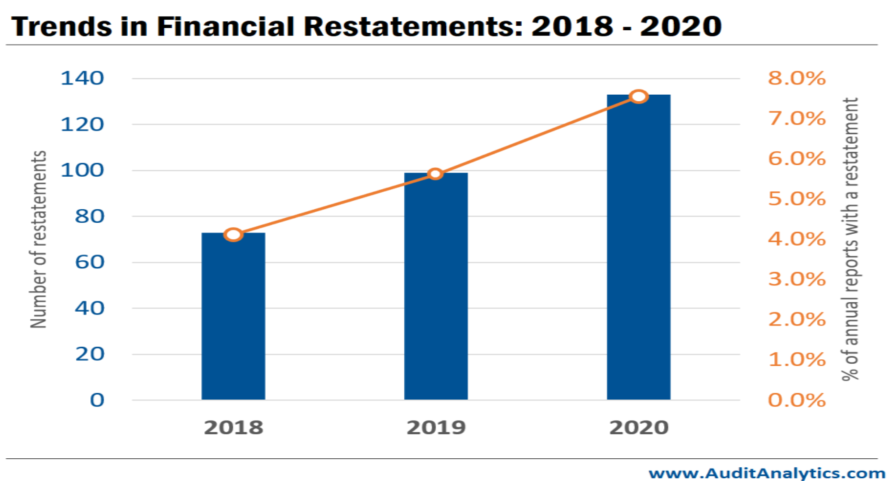

Fig. 3. Trends in financial restatement :2018-2020

In addition, the top restatement issues in 2020 can be shown as follow:

Table .1: Top Restatement Issues: 2020

Rank	Accounting Issue	Frequency
1	Liabilities and accruals	24.1%
2	Revenue recognition	14.3%
3	Leases	12.0%
4	Inventory	11.3%
5	Debt and equity Securities	11.3%
6	Intercompany issues	10.5%
7	Tax matters	8.3%
8	Mergers and acquisitions	8.3%
9	Assets classification	8.3%
10	Cash flow classification	7.5%

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Consequently, the term dataset covers the listed firms in London Stock Exchange and the period from 2018 to 2020, especially the firms that restated its financial statements even just once during the study period. Where every firm in this time period restated one time only. In this regard, the final sample of study is 304 firm year observations.

3.2 Variables definition

To cope with the techniques of Machine Learning that has been relied upon the most used indicators in the related studies. That may help in classifying the restatement into two groups: restatement as correcting unintentional error and restatement coded as intentional misstatement. Referring to the studies [22, 4,13,6,5,23] 16 variables are chosen as possible indicators of financially statements. Consequently, the variables used in testing are described in Table 1.

Table 2: Variable definitions

Variables	**Explanation**
Restatement Types UE indicator using machine learning (ML)	dummy variable is equal to 1 if the machine learning tools classified the restatement as correcting unintentional error and 0 if the restatement coded as intentional misstatement;
Non-Machine Learning Classifiers	
Magnitude	equal to 0 when the cumulates change in net income is greater than sample median, and 1 otherwise.
Direction	equal to 0 when restatements correct net income overstatement, and 1 otherwise.
Time	equal to 0 when the number of restated days is greater than the sample median, and 1 otherwise.
Revenue Recognition	equal to 0 when revenue recognition issues are corrected, and 1 otherwise.
Severity	equal to 0 when the summary restatement severity measure is greater than the sample median, and 1 otherwise.
Restatement	dummy variable is equal to 1 if the firm observation restated its financial statement and 0 otherwise;
Intentional Misstatement (IM)	dummy variable is equal to 1 if the firm observation restated its financial statement because of intentional misstatement.
X1	Total accruals which is the difference between net income and the operating cash flow.
X2	Asset intensity, which can be calculated as the total assets divided by total revenue.
X3	Financial Leverage, which can be calculated as the total liabilities divided by total assets.
X4	Loss, which is dummy variable coded 1 for the loss-making firms and 0 otherwise.
X5	Return on total assets: calculated by a company's net profit divided by its total assets.
X6	Net income: represents the fiscal period income or loss reported by a company.
X7	Auditor's size: dummy coded 1 for a Big 4 auditor, 0 otherwise.
X8	Log of total assets (Size): natural logarithm of a firm's total assets at the end of the fiscal year.
X9	Log of net sales: natural logarithm of a firm's net sales during the fiscal year.
X10	Inventories; the value of inventories in the financial statements.
X11	Long term debt.
X12	Market to book value.
X13	Operating cash flow.
X14	Sales growth; [total sales - total sales in the previous year]/ total sales in the previous year.
X15	Cumulative change in net income; The cumulative change in net income reported by Audit Analytics for the restatement period scaled by total assets in the first restated year.

3.3 Data analysis and empirical results

In this part of research, the empirical results can be divided into two stages; the first one assigned to discuss the results of machine learning results, and then the second stage assigned to discuss the comparison between Machine Learning Techniques Results and Non-Machine Learning Classifiers as follow:

3.3.1: Factor analysis & Correlation Matrix:

This part of the research aims to test the Non-Machine Learning Classifiers indicators (i.e, Magnitude, Direction, Time, Revenue Recognition and Severity). Table 2 provide information on the factor analysis (varimax rotation) used to create an additional, composite, measure of severity to capture correlated aspects of restatement severity in a single measure as follow:

Table 3: Factor Loading for Summary Restatement Severity Measure

Component	Factor Loading
Magnitude	-0.568
Direction	0.573
Time	0.268
Revenue Recognition	0.687

Table 4: Correlation Matrix for Summary Restatement Severity Measure and Components

	Magnitude	Direction	Time	Revenue Recognition	Severity
Magnitude	1	-0.208***	-0.081***	-0.135***	-0.785***
Direction	-0.086***	1	-0.085***	0.079***	0.121***
Time	-0.041	-0.081***	1	0.107***	0.381***
Revenue Recognition	-0.026	0.082***	0.103***	1	0.161***
Severity	-0.271***	0.171***	0.342***	0.189***	1

*** indicate two-detailed significance at the p < 0.01.

Table 3. presents Pearson (Spearman) correlations are presented below (above) the diagonal. The correlation coefficients of the above matrix are significant for all listed variables.

3.3.2 Machine Learning Techniques Results:

Table 4. presents the classification results obtained from the algorithms of machine learning (i.e. SVM, NV Naive Bayes, and K-means) as follow:

Table 5: Classification Results for the algorithms of machine learning

Model	**Accuracy (%)**	**Type I error (%)**	**Type II error (%)**
K-means	83.9	18.1	16.1
Naïve Bayes	82.4	17.3	17.6
SVM	81.6	17.8	18.4
Type I error: Refers to the error of coding ‘‘restatement as correcting unintentional error’’ when it is an ‘‘restatement coded as intentional misstatement’’.			
Type II error: Refers to the error of predicting ‘‘restatement coded as intentional misstatement’’ when it is ‘‘restatement as correcting unintentional error’’.			

The classification of restatement reports is best handled by K-means, Naïve Bayes and SVM, according to prediction accuracy, Type I error, and Type II error rates. Moreover, the mentioned techniques used for predicting by the optimal types of restatement types (i.e. restatement as correcting unintentional error & restatement coded as intentional misstatement) to the study sample for the purpose of comparing the results of Machine Learning Classifiers results with the Non-Machine Learning Classifiers results in the next section of this research.

3.3.3: Descriptive statistics

Table 5 presents the descriptive statistics depending on compared results of the unintentional errors observations (UE) and the Intentional Misstatement observations (IM), where conduct the means (t-test) and medians (Wilcoxon rank sum test) of firm-years observations. The results revealed significant difference either in the means or the medians, where the variables' means (total accruals, financial leverage, return on assets, auditor's size, market to book value and Cumulative change in net income) are significant at the level (P < 0.01). In addition, the results showed significant difference in the variables' medians (auditor's size, market to book value, operating cash flow, sales growth and Cumulative change in net income) are significant at the level (P < 0.01).

Table 6: Descriptive statistics for restatement correcting UK financial statement in time period 2018-2020.

	Restatement Firm Years			**Unintentional Error (UE)**			**Intentional Misstatement (IM)**			**Mean diff. t**	**Median diff. z**
	n	Mean	S.D.	n	Mean	S.D.	n	Mean	S.D.		
Total accruals	304	3,871.26	7,521.45	258	2,875.36	6,781.42	46	3,621.89	7,125.23	-2.18***	0.43
Asset intensity	304	3,568.44	6,821.32	229	3.671.47	5,791.69	75	3,462.71	6,792.3	0.929	0.78

									5		
Financial Leverage	304	0.23	0.32	248	0.25	0.35	56	0.28	0.31	3.25***	0.78
Loss	304	0.55	0.48	232	0.51	0.50	72	0.53	0.49	0.396	0.33
Return on total assets	304	-0.49	0.98	241	-0.58	0.35	63	-0.38	0.17	-3.41***	0.55
Net income	304	85.48	1.25	244	75.36	3.41	60	68.41	3.21	1.071	0.39
Auditor's size	304	0.62	0.32	243	0.59	0.45	61	0.57	0.21	-3.87***	-3.21***
Log of total assets	304	7.25	2.26	236	6.92	3.67	68	5.29	2.92	0.607	0.67
Log of net sales	304	6.28	3.41	257	5.98	1.01	47	5.88	2.21	1.211	0.26
Inventories	304	95.26	3.25	245	88.18	4.28	59	81.39	3.67	0.899	0.27
Long term debt	304	4,627.45	125.36	230	3,692.42	141.27	74	3,821.35	111.15	0.14	0.32
Market to book value	304	1.95	3.81	247	1.87	2.47	57	2.36	1.25	-2.69***	-2.97***
Operating cash flow	304	125.36	23.47	255	138.21	36.88	49	122.47	15.26	0.364	3.25***
Sales growth	304	0.55	0.36	258	0.48	0.28	46	0.51	0.31	0.522	-3.66***
Cumulative change in net income	304	-16,825.31	25,321.89	228	-19,461.25	22,356.47	76	-18,736.88	21,627.11	3.82***	9.81***

*** indicate two-detailed significance at the p < 0.01.

3.3.4: Multivariate analysis

In practice, the algorithm analyzes relationships between variables and uses the sigmoid function to assign probabilities in discrete form. The samples are split into two groups for binary predictions based on a cut-off of 0.5. Group A includes samples above 0.5, and group B includes samples below 0.5.

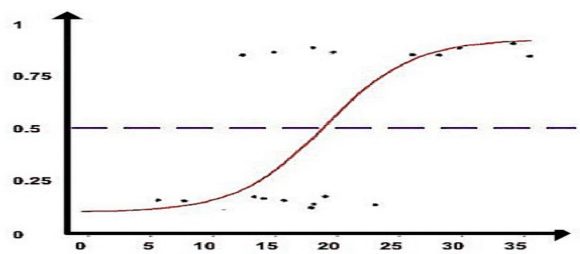

Fig. 3. Sigmoid function for binary predictions based on a cut-off of 0.5.

Tables 6,7,8 report the logistic regression test results of the effect of machine learning techniques on the intentional misstatements, restatements and the intentional misstatements on the restatements, respectively.

The results of table 6 showed the positive significant effect of machine learning techniques (i.e. K-means, Naïve Bayes, SVM) on the intentional misstatements. Which means that, using machine learning techniques helps in determining the intentional misstatements. In addition, there is a positive significant effect of some non-machine learning classifiers, such as: magnitude and revenue recognition. Consequently, I can accept the first hypothesis on the alternative form as following:

H1: there is a significant positive relationship between using machine learning techniques and the auditors' ability to evaluate the intentional misstatements.

The results of table 7 showed the negative significant effect of machine learning techniques (i.e. K-means, Naïve Bayes, SVM) on the restatements. Which means that, using machine learning techniques helps in avoiding the restatements. In addition, there is a positive significant effect of some non-machine learning classifiers, such as: magnitude, revenue recognition and severity. Consequently, we can accept the second hypothesis on the alternative form as following:

H2: there is a significant negative relationship between using machine learning techniques and the restatements.

Table 7: Logistic Regression for testing H1

	Test	**Panel A**			**Panel B**		**Panel C**	
		n	Z	Sig.	z	Sig.	z	Sig.
Machine Learning (K-means)	Logistic	304	3.41	***				

Machine Learning (Naïve Bayes)	Logistic	304			2.87	***		
Machine Learning (SVM)	Logistic	304					3.25	***
Non-Machine Learning Classifiers	Logistic							
Magnitude	Logistic	304	2.87	***	3.81	***	2.95	***
Direction	Logistic	304	0.58	NS	0.73	NS	0.83	NS
Time	Logistic	304	0.82	NS	0.56	NS	0.6	NS
Revenue Recognition	Logistic	304	3.21	***	3.35	***	3.47	***
Severity	Logistic	304	0.8	NS	0.8	NS	0.69	NS

Table 8: Logistic Regression for testing H2

	Test	Panel A			Panel B		Panel C	
		n	z	Sig.	z	Sig.	z	Sig.
Machine Learning (K-means)	Logistic	304	-3.85	****				
Machine Learning (Naïve Bayes)	Logistic	304			-2.97	***		
Machine Learning (SVM)	Logistic	304					-3.27	***
Non-Machine Learning Classifiers	Logistic							
Magnitude	Logistic	304	3.18	***	2.66	***	0.6	NS
Direction	Logistic	304	0.79	NS	0.82	NS	0.7	NS
Time	Logistic	304	0.67	NS	0.69	NS	0.59	NS
Revenue Recognition	Logistic	304	2.57	***	0.71	NS	3.88	***
Severity	Logistic	304	0.65	NS	2.37	***	2.99	***

Finally, the results of table 8 showed the positive significant effect of intentional misstatements on the restatements. Which means that, the existence of intentional misstatements leads to increase the need for restatements. In addition, there is a positive significant effect of some non-machine learning classifiers and control variables, such as: loss, direction, revenue recognition and cumulative change in net income. Consequently, we can accept the third hypothesis on the alternative form as following:

H3: there is a significant positive relationship between intentional misstatements and the restatements.

Table 9: Logistic Regression for testing H3

	Test		n		Z		Sig.
intentional misstatement (IM)	Logistic		304		2.85		***
total accruals	Logistic		304		0.66		NS
Lev	Logistic		304		0.73		NS
Loss	Logistic		304		3.86		***
ROA	Logistic		304		0.74		NS
Direction	Logistic		304		2.56		***
Time	Logistic		304		0.72		NS
Revenue Recognition	Logistic		304		2.27		***
Cum.NI Change	Logistic		304		3.81		***
***, **, ** indicate two-detailed significance at the $p < 0.01$, $P < 0.05$ and $p < 0.1$ levels, respectively.							
Model used in multivariate tests unless otherwise noted:							
Restatement = β0 + β1 intentional misstatement (IM) + β2 total accruals +β3 Lev + β4 Loss + β5 ROA + β5 Cum.NI Change + ε (9)							

3.3.5 Comparison between Machine Learning Techniques Results and Non-Machine Learning Classifiers results:

Based on the above results, the machine learning techniques (i.e. K-means, SVM and Naïve Bayes) is outperformed the Non-Machine Learning Classifiers. Consequently, we conclude some comparisons between the Restatement type using Non- ML Classifiers and Predicted restatement type using ML as following:

Table 10: Compared means between Restatement type using Non -ML Classifiers and Predicted restatement type using ML

	Variables	**Mean**	**T**	**Sig. (2-tailed)**
Pair (1)	Restatement type using Non -ML Classifiers	1.222	5.137	0.000
	Predicted restatement type using ML (i.e. K-means)	1.177		
Pair (2)	Restatement type using Non -ML Classifiers	1.222	7.404	0.000
	Predicted restatement type using ML (i.e. Naïve Bayes)	1.156		

Pair (3)	Restatement type using Non -ML Classifiers	1.177	10.366	0.000
	Predicted restatement type using ML (i.e. SVM)	1.110		

Table 9. presents in pairs (1,2,3) shows the results of compared means between the Restatement type using Non-ML Classifiers and predicted restatement type using machine learning. These results indicate that the means of predicted restatement type using machine learning are lower than Restatement type using Non-ML Classifiers. Which means that, Restatement type using Non-ML Classifiers biased toward the ‘‘unintentional error’’, where the difference is significant because of the high accuracy of machine learning techniques.

4. Conclusions

In this study, we looked at the relationship between the Machine Learning Approach, intentional misstatement, restatement, and intentional misstatement on restatement in listed firms on the London Stock Exchange. In order to show the role of auditors' risk assessments, material misstatement, and type Machine Learning algorithms. As well as, how machine learning contributes to restatement classification. When a supervised learning algorithm can classify a fraudulent transaction from a non-fraudulent one, and then predict whether the next transaction is fraudulent or not. The machine learning techniques (i.e., K-means, SVM, and Naïve Bayes) outperform the non-machine learning classifiers.

The findings revealed that, the positive effect of machine learning techniques, such as: K-means, Naïve Bayes, and SVM, on intentional misstatements outweighed the positive significant effect of intentional misstatements on restatements. Implying that, the presence of intentional misstatements increases the need for restatements. Finally, predicted restatement type using machine learning is lower than restatement type using non-ML classifiers. Which means that, restatement type using non-ML classifiers is biased toward "unintentional error," where the difference is because of the high accuracy of machine learning techniques.

The means of predicted restatement type using machine learning (1.177, 1.156, and 1.110) are lower than the means of predicted restatement type using non-ML classifiers (1.222, 1.222, and 1.222). Indicating that, restatement type using non-ML classifiers is biased toward "unintentional error". Where the difference is significant due to machine learning techniques' high accuracy

5. Recommendations

The research recommends can also measure the impact of the machine learning algorithm, implemented by auditors on financial performance in the public sector and increase the transparency of financial statements.

Conflicts of Interest Statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers’ bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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