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Predicting Auditor Opinion and Stock Price Using Machine Learning Techniques: Evidence from Egypt

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Abstract

The research aims to predicting auditor opinion and stock price using Machine Learning. Techniques the Decision Tree (DT), Neural Network (NN), Bayesian Network (BN), Support Vector Machine (SVM), K-Nearest Neighbors (K-NN), Rough Sets (RS), and Random Forest (RF) are the most widely used machine learning approaches that deal with financial variables. Additionally, this study use Probit Regression. The data of this study consists of 758 firm-years of Egyptian companies listed on Egyptian Stock Market from 2012 to 2022. The results revealed that positive relationship between auditor opinion and stock prices, audit opinion significantly different between the actual value and the predicted using machine learning techniques and stock price significantly different between the actual value and the predicted using machine learning techniques. The research recommends measuring the impact machine learning algorithms and continuous auditing, audit quality, and internal auditing in the Egyptian environment.

Keywords: Auditor Opinion, Stock Price, Machine Learning, Decision Tree (DT), Neural Network (NN), Bayesian Network (BN), Support Vector Machine (SVM), K-Nearest Neighbors (K-NN), Rough Sets (RS), and Random Forest, Probit Regression.

1. Introduction

Over the past few years, studies about auditors' perspectives have been more and more common. When "substantial doubt" emerges over the client firm's continued viability throughout the course of the following year, the auditor is required by Statement of Auditing Standards (SAS) No. 59 to disclose this in the audit predicting auditors' opinions report (Zarei, et al. 2020). This extra market information on the auditor's professional judgment of the danger that the company may not survive in the near future is provided by the auditor's message and (Kausar et al., 2017).

When it comes to auditor reporting on financially distressed clients, the global financial crisis has led to a large rise in business failures. Concerning issues that need to be addressed right away include the unique risks that businesses encountered during the height of the credit and liquidity crises in 2007 and 2008, as well as the role that auditors played in issuing warnings about these issues (Zarei, et al, 2020).

These concerns led to a series of high-level inquiries on the operation and effectiveness of external auditing, both locally and internationally, with an emphasis on auditors' assessments and reports on a firm's capacity for survival as a going concern. Going-concern opinions may continue to be issued at high rates due to higher levels of customer failure risk in addition to increased scrutiny from regulators of managers regarding disclosure of going-concern issues resulting from corporate failures, with auditors adapting to any increase in director relates to as well as managing risk associated with expected evaluation from firm inspections (Carson et al., 2019).

As a result, the likelihood of corporate collapse is critical information for creditors, shareholders, and management, and a firm's position as a "going concern" is vital to both internal and external stakeholders.

1.1 Research Problem

Information that is crucially vital to shareholders, creditors, and management is also crucial to the firm's position as a "going concern" for both internal and external stakeholders. The value of a company's stock may be impacted by the audit opinion on its financial accounts. A favorable audit opinion will contain information that can drive up the value of the company's stock, whilst a negative audit opinion will contain information that can drive down the value of the company's stock. Therefore, the audit result report from the auditor should include facts that can affect the company's stock price (Ramadhani & Sulistyowati, 2020).

The prevailing belief is that since the audit opinion represents a warning about the viability of the company, investors should find value in it. Due to their access to internal company information and proficiency in evaluating going-concern issues, auditors are able to give the market an indication (Rena, et al., 2016).

The requirement for auditors to assess and report on an entity's ability to survive as a going concern has drawn more attention in recent years (Strickett & Hay, 2015). Empirical show that these disclosures genuinely influence investors' pricing decisions would strengthen the case for maintaining and, possibly, even strengthening these disclosures. Prior studies, such as those by (Chung et al., 2019; Hardi et al. ,2020; Strickett & Hay ,2015), have only offered conflicting evidence of a relationship between going-concern decisions and share price adjustments. These studies' ambiguous conclusions may be due to their implicit assumption that all qualified going-concern opinions affect asset prices equally.

In this sense, going-concern qualifications have undergone considerable pricing revisions since the audit opinion was disclosed. Despite this, the stock prices were only marginally negatively impacted by qualified audit opinions, and the strength of the impact varied depending on the kind of qualification (Chung et al., 2019). Stock returns were not significantly impacted by the public disclosures of audit qualifications, particularly going-concern qualifications (Hardi et al., 2020).

As a result, firms that could be adversely affected by the unfavorable audit opinion frequently shop the auditor's opinion in search of a more favorable audit opinion. In such a scenario, market participants are unable to detect a transition and are not alerted to possible flaws in financial reporting. In a similar vein, stock price evaluation is crucial for the financial markets to make wise decisions and it is a vital component of stock trading techniques. While they can grasp the trend patterns of stock prices and aid investors in developing effective investment strategies, accurate stock price predictions are of significant practical relevance. Then, effective trading techniques can be used to provide higher profits with lower risk (Zhang et al., 2022).

In addition, forecasting movements in stock prices is simple when the stock market is remarkably steady and behaves in a predictable way. However, when specific political or economic circumstances have an impact on the global trading networks, it gets more and more difficult. For instance, market volatility has significantly increased due to the ongoing crisis between Russia and Ukraine, making it practically impossible to predict what will happen tomorrow (Reuters, 2022; The Guardian, 2022; The New York Times, 2022).

In recent years, accounting has made substantial use of machine learning, an effective branch of artificial intelligence. While allowing financial organisations to spot fraudulent transactions, it aids management in their decisions regarding credit scoring, ranking, and granting. Thanks to its ability to manage vast volumes of data while also allowing non-linearities in the data, machine learning has emerged as a leader in statistics. In recent decades, substantial research in accounting has focused on computational intelligence (Ozbayoglu et al., 2020).

On Egypt, the researcher believed that the economic environment has many fluctuations as result of the bad economic situations and the accumulated debt in favour of the International Monetary Fund, which lead the Egyptian firms to shop the auditor opinion for the purpose of achieving stable stock prices in the capital market. Consequently, the motivation of this research stem from the fluctuated Egyptian environment, where it is so fertile for using machine learning to predict the auditor opinion and the stock price movements, so as to make sure about the right tendency of the relationship between the auditor opinion and stock prices, the 758 firm-years of Egyptian firms listed on the Egyptian Stock Market from 2012 to 2022 make up the data for this study. After eliminating businesses engaged in the banking and finance industries, which have numerous characteristics missing, the sample forms.

1.2 Research contribution

This research will contribute to the accounting literature in many ways: Firstly, shows the relationship between the auditor opinion and stock prices in the Egyptian environment. Secondly, deals with the predicting errors of the auditor opinions and the stock prices in the Egyptian stock market using machine learning. Thirdly, tries to identify the significant differences among the predicted values of the auditor opinions and the stock prices and the actual values. Last but not least, efforts were made to close the gap by classifying the audit reports into three categories: unqualified, unqualified with justification, and qualified using a relatively modest dataset.

The remaining portion of the research is structured as follows: The relationship between the auditor's opinion and the stock price, as well as the function of machine learning techniques to forecast the auditor opinion and stock price is used in Section 2 to show the theoretical structure and hypothesis creation. The data and research techniques are illustrated in Section 3. The data evaluation and empirical findings are displayed in Section 4. The researchers then report their findings and plans for further study.

2.Theoretical Framework& Hypotheses Development:

2.1. The relationship between auditor opinion and stock price:

The price that is paid when a stock is purchased and sold on the stock market is known as the stock price. The hypothesis of efficient markets (EMH), which Fama devised and proposed, contends that markets are effective and that asset prices currently accurately, efficiently, and timely represent any information about the underlying value of assets. The idea of predicting financial time series was first put forth by non-random walk theory, but the actual market is not effective and error-free (Liu et al,2023).

So, anticipating stock fluctuations with accuracy can offer investors investment profits and reduce investment dangers. Forecasting future stock prices in financial time series prediction is challenging, nevertheless, because of the volatility of financial markets (Oncharoen et al., 2018).

The following groups of factors can be utilized to forecast the stock market: (1) sentiment-related elements (2) indexes that measure stock price, such as the Standard & Poor's 500, the Shanghai Securities Exchange Composite (SSEC) index, and others; (3) indicators that measure liquidity; (4) technical measures; and (5) previous trade-based indicators, such as volatility, revenue, as profits, prior stock price, and others (Liu, et al ,2023).

Numerous researches (Rena, et al., 2016; Robua et al., 2015; Hoti et al., 2012) have been conducted to determine how an audit opinion on financial statements affects the company's stock price. Otherwise (Hoti et al., 2012) deduced from the findings of their study that the movement of stock values is influenced by auditors' opinions. In their research report (Robua et al., 2015), made the unequivocal claim that the audit report's information significantly affects stock return (Rena, et al., 2016), and came to the additional conclusion in their study that the investor's choice is supported by the auditor's opinion.

Ha. et al. (2016) identified the correlation between non-financial information, including the size of the firm, auditing firm, going-concern opinion in the past year, and auditors' judgment on audit report, and financial ratios. The research analyzed the financial statements, auditors' opinion, and financial statements comments for listed enterprises in Vietnam that both obtained and did not receive a qualified audit report. The results of using binary logistic models show that the ratio of earnings before taxes (EBT), the ratio of financial leverage, and the going-concern opinion from the prior year are each factor that affects auditors' opinions on audit.

According to Al-Attar, K. A. (2017), higher audit quality leads to better financial performance of the firm, which is reflected in their stock prices. Audit has an immediate effect on stock prices of firms in the Amman stock market.

For firms listed on the stock exchange in Tehran (Zarei et al. ,2020), analyze the extent to which a model based on financial and nonfinancial criteria forecasts auditors' decisions to submit qualified reports of auditing. Non-financial factors including business performance, the type of audit firm, and auditor turnover have an impact on the issue of audit reports. Through the use of 11 important financial measures, a total of 480 observations were assessed using an integrity model.

The findings showed that financial ratios and the kind of audit firm (the national audit organization vs. other local audit firms) had a strong explanatory power in describing qualifications in audit reports. Regression modeling is used to assess the estimated model's predictive accuracy for the probability of sound and qualified opinions.

The influencing variables of audit findings were examined from four angles by (Zeng, & Yang, 2021): the market environment, non-financial indicators, financial indicators, and market relative value. By creating a system for predicting the audit opinion, SMOTE oversampling technology was used to address the issue of sample imbalance, and deep residual learning and convolutional neural networks were coupled to forecast the audit opinion.

Awad, (2022) conducted a study in which several commercial private banks in Iraq were put through a series of financial tests to show the reality of the situation. The researchers used a range of technologies to search for data, such Decision tree, ID3, Naive Byes, and Random Forest, in order to select the best appropriate ratios to support the auditor's conclusion in his report on the firm's sustainability. The analysis's findings demonstrated that the ratios of Debt Ratio, Return on Assets, and Equity Debt Ratio are more accurate at predicting the state of the bank.

Feng, et al. (2023) investigate when auditors take stock price information into account while examining the financial reports of their customers. Together, the research demonstrates that auditors gain knowledge from their customers' stock prices, and that this knowledge enhances the quality of the audits they perform. Particularly when the stock returns are low in comparison to pre-audited earnings, the audit adjustments are strongly correlated with the misalignment between customers' yearly stock returns and pre-audited earnings. The organization focuses on customers whose stock prices include more sensitive trader information. Additionally, when stock prices include more private information from traders, including stock price information in audits enhances audit quality (Feng et al, 2023).

A connection between audit adjustments and stock return residual that is positive offers essential, according to (Feng, et al.,2023), When inspecting their clients' financial reports, auditors also use: (1) Their own private knowledge and (2) Public news about their clients in addition to the traders' private information in stock prices.

Insofar as these two pieces of information are positively connected with the stock prices of the customers, the auditors' utilization of these two categories of information could likewise result in a favorable correlation between stock return residual and audit adjustments.

As a result, differing interpretations of the findings of earlier studies regarding the impact of audit views on stock prices remain. According to the aforementioned evaluation of the literature, the study's initial hypothesis is:

H1: Audit opinion positively affects the stock price of the company.

2.2. Machine learning techniques and its role in predicting the auditor opinion and stock price:

The procedure allows for the discovery of complicated relationships and patterns that would be difficult for humans to find using traditional statistical techniques. In general, design science can be thought of as a subset of machine learning. Whose goal is to create practical tools to aid in the resolution of significant issues, as opposed to natural and social sciences, which aim to create theories and put them to the test (Kogan et al., 2019).

Machine learning is the automatic identification of significant data patterns. Over the past few decades, it has developed into a widely utilized technology that is employed for practically every activity that calls for information extraction from huge data sets. Machine learning methods commonly used for forecasting in the stock market in the previous research consist of (1) Artificial Neural Networks, also known as ANN; (2) random forest methods (RF); (3) Support Vector Regression, also known as SVR; (4) Adaptive Boosting (Adaboost); (5) Gradient Boosting Decision Trees (GBDT); and (6) deep neural network models (DNN). (Li et al., 2019; Henrique et al., 2018; Ciner et al., 2019; Jin et al., 2020; Ampomah et al., 2020; Sun et al., 2020a, 2020b; Gu et al., 2021 ;Ghosh et al., 2021; Mohapatra, 2021b).

Because prediction is frequently their principal usage, machine learning algorithms have a very high potential to enhance prediction tasks (Gu et al. 2020). However, they may not be as good at making predictions outside of the sample as other models that are frequently employed in accounting research, such as logistic regression. Because they need less assumption about the method used to generate the data, machine learning techniques may also lead to predictions that are more accurate than those generated using other techniques (Mullainathan and Spiess, 2017). Due to their adaptability and suitability for approximating complex and unknowable data generating processes, they are flexible (Gu et al. 2020).

An approach was put forth by (Sánchez et al., 2019) to recognize and assess any changes in the auditor's behavior. The strategy relies on the use of assembled classification trees, especially when bagging and boosting techniques are used. When the results of the two methods are compared, it becomes clear that the assembly with bagging generated superior results. This process' effectiveness was assessed using logistic regression. The comparison shows that bagging results and logit results are generally equivalent, despite the former's greater specificity and the latter's greater sensitivity.

Alareeni, (2019) gave a full study of the company's performance and the auditors' assessment of its viability. In particular, it demonstrates that neural network models produce superior results and are the most accurate approach to predict a company's future position failure or non-failure. Artificial intelligence technique is superior to auditors' going concern opinions in this case.

Sanchez et al, (2020) developed a new model for predicting audit views for consolidated financial statements using a multiple-layer perceptron artificial neural network and a sample of a group of Spanish enterprises. Analysis indicated that the developed approach predicted the audit opinion with a precision of more than 86%. There were significant differences between the most significant factors used to forecast the audit opinion for every account and those utilized when using unorganized financial statements when utilizing consolidated finances, which turned the variables directly relating to the sector, size of the group, auditor, and board of directors into the primary explanations of the prediction.

Support vector regression was employed in the study of (Manurung et al., 2023) to analyze the likelihood of bankruptcy. There are 6 variables from 17 Indonesian businesses for the years 2016 to 2018. The model developed using support vector regression predicts good performance because of its high coefficient of determination in compared to other studies. The likelihood of bankruptcy is appropriately predicted by the model, according to the R2 value of 0.5014. The study discovered that adopting a more sophisticated machine learning model and adding more data might theoretically boost performance.

The prediction models were built through decision tree models (DT), the support vector machine (SVM), the k-nearest-neighbors algorithm (K-NN), and Rough Sets (RS) to compare the effectiveness of four data mining algorithms in the forecasting of audit opinions on firm financial statements (Saeedi, A.,2021; Zeng, et al.,2022).

Aly et al. (2023) investigate the relationship between auditors' judgments of significant errors and restatement risks and machine learning algorithms. A primary focus is also on the influence of machine learning algorithms (SVM, Naive Bayes, and K-means) on restatement and misrepresentation in London firms. The findings indicated that the deliberate misstatements were positively and significantly affected by machine learning approaches (K-means, Naive Bayes, and SVM), indicating that utilizing machine learning techniques can aid in identifying purposeful misstatements. The findings also indicated that the same algorithms (K-means, Naive Bayes, and SVM) had a substantial negative impact on restatement, indicating that utilizing machine learning techniques can assist prevent restatement.

Because the models built by these four strategies predict the audit perspectives with reasonable accuracy, the SVM models produced showed the best results both in terms of overall forecasting success levels and both Type I and the second error types. Additionally, all models created using various algorithms exhibit their best performance when forecasting going-concern changes.

We can demonstrate how predicting audit views of publicly traded businesses are important for preventing market risk. Numerous improvements can be put into practice to raise audit efficiency, increase audit quality, and sharpen auditor insight by utilizing machine learning techniques.

The researchers might draw a conclusion about the discrepancy between conventional ways of forecasting the auditor opinion and intelligent approaches that rely on machine learning based on the aforementioned factors. Thus, the following might be developed as the second hypothesis of this study:

H2: Audit opinion is significantly different between the actual value and the predicted using machine learning techniques.

Various stakeholders' investment decisions are heavily influenced by the financial reports and audit reports that listed companies periodically release. The phrase "audit report" means to the statement in writing of the certified public accountants' (CPA) audit opinion provided on the financial information of the audited company based on completing the audit work in accordance with the audit standards (Zeng et al,2022).

The audit of financial statements is tasked with expressing an opinion regarding if the financial statements reflect the financial position, operational outcomes, and cash flow of the audit and whether they have been set up in accordance with the applicable accounting standards. Due to the limitations of their professional knowledge, time, and other variables, users of financial statements find it difficult to effectively analyze and precisely assess the legitimacy and conformity of firm financial statements. Regarding the assurance documentation of the company's financial status, operational performance, cash flow, and other information, CPA, a third party that is separate from the audited firms and stakeholders, issues relevant audit opinions to strengthen the reliability of financial data of listed firms (Zarei, et al,2020; Saeedi, 2021;Zeng et al,2022).

The subject of stock price prediction has attracted significant attention for many years and spans a variety of disciplines, including corporate finance, investment analysis, financial econometrics, and behavioral finance (Chavarnakul & Enke, 2009). Fundamental analysis and technical analysis are the two traditional methods used to forecast stock market trends (Vui et al., 2013). According to (Chen et al., 2017), fundamental analysis takes into account microeconomics, the industrial environment, financial conditions, financial news, etc.

Technical analysis is a set of techniques for predicting the potential price of a financial asset while taking into consideration historical market data, in particular exchanged volume and stock price movement (Wei et al., 2011; Yamamoto, 2012).

Probabilistic thinking is a type of technical analysis. Instead of trying to accurately forecast an occurrence, it looks for non-random regularities. Although the actual application of technical analysis may result in a loss in a single instance, it will be beneficial when used consistently over a large enough sample size of events. Modern statistical techniques, machine learning, and artificial intelligence are improving traditional technical analysis. Artificial Neural Networks, Recurrent Neural Networks, Genetic Algorithms, Evolutionary Computing, Fuzzy Systems, and other methods are some of these methods (Bisoi & Dash, 2014; Kazem et al., 2013). Some practitioners might make a distinction between a quantitative finance approach (with statistics and AI falling under the latter) and a technical analysis method. We see no need for this distinction because all of the material on which our work is based deals mathematically with technical analysis principles.

Numerous studies have therefore attempted to forecast it. For example, Carl Gold suggested a neural network (NN) model to forecast high frequency FOREX pricing (Kristjanpoller & Minutolo, 2015). Recurrent Reinforcement Learning (RRL) was used to train the neural network, and the first author evaluated the effectiveness of 1- and 2-layer NN. The impact of neural network weights on price prediction was also shown by the author.

When selecting when to buy or sell stocks, (Cervellóet al, 2015) suggested risk-adjusted profitable stock trading principles. The outcomes comprised the likelihood of profit in each transaction and the most loss that could be absorbed under the trading rules. They used 91,307 intraday observations from the US Dow Jones index for their investigation, which took the unpredictability out of the outcome. By merging 96 configurations, they parameterized their training procedures, and the outcomes were tested over three sub periods. They also repeated their analysis on the German DAX and the British FTSE, which demonstrates that the proposed trading rules have a larger return on investment in the European index than in the US index.

In five stock markets in Southeast Asia, (Tharavanij et al, 2015) investigate the profitability of technical trading methods. The index of relative strength (RSI), average move convergence-divergence, random oscillator, on balanced volume, as well as the movement indicator were used to evaluate the efficacy of the buy-and-hold strategy. Their findings show that, whereas Thailand's markets gain from technical trade restrictions, the markets of Singapore, Indonesia, Malaysia, and the Philippines do not.

Ngoc et al, (2023), investigates the effects and relevance of company features on the reliability of the financial statements of companies listed on the Vietnamese stock exchange. Between 2014 and 2020, data from 2225 publicly traded corporations was analyzed using models of regression and machine learning approaches. According to the findings of the study, the efficacy of financial statements is highly related to business revenue, number, and the number of members of the board of directors. On the contrary, there is a negative correlation between the timing of enterprise listing, policy on dividends, and state ownership. According to the findings, the most important elements affecting financial statement quality are revenue, income after tax on total assets, ownership by the state, and firm size. For market players and policymakers, this result has practical implications for enhancing the transparency and caliber of financial reporting.

It can be argued that ANN is an excellent technique for forecasting financial market forecasts. An ANN aims to clearly recreate the networks of nerve cells. It offers the ability to handle large, highly complex, dynamic data sets found in the stock market. It is a strategy that may be used to learn statistical parameters, extract data, detect patterns, forecast, and forecast (Shanmuganathan, 2016). It is utilized to tackle a challenge brought on by its changeable nature by combining factors from fundamental and technical analysis to forecast stock market prices (Selvamuthu et al, 2019).

According to (Selvamuthu et al, 2019), tick data can be used to anticipate the stock market. They have demonstrated that there are three common approaches: technical analysis, time series forecasting (a more conventional approach), and machine learning. SVM is one of the additional ML techniques for stock market forecasting. It is a non-linear approach created in the 1990s for regression and classification applications.

In order to predict the stock market, (Gururaj et al, 2019) conducted an examination utilizing two machine learning methods. The study's major objective was to predict stock using Linear Regression (LR), a fundamental method for obtaining a linear trend, and Support Vector Machine (SVM), and an advanced feature. The end day price was forecast using the Statistic Language R generated by the RStudio environment for development and data on stocks from the Coca-Cola Company's website from 2017 to 2018. The Mean Absolute Error, Mean Absolute Percentage Error, and Root Mean Square Error were utilized to assess performance in experiments using the Time-Series Prediction Methodology and the Sliding-Window Method. SVM outperforms LR techniques because the error levels are lower.

Zhang& Chen (2023), offer a novel two-stage forecasting framework that includes a decomposition method, a nonlinear ensemble tactics, and three distinct machine learning models. In the first stage, vibrational mode decomposition (VMD) is utilized to decompose the stock price series of time into a limited number of sub-series. Then, to forecast decomposed sub-series, three unique machine learning models are applied separately: (SVR), extreme (LM), and (DNN). The initial stock price projections are produced by combining the sub-series predictions acquired from each different prediction model. In the second stage, preliminary stock price projections are combined using a nonlinear ensemble technique built on ELM. The suggested two-stage model is evaluated for correctness, compared for improvement percentage, and subjected to a statistical test in order to demonstrate its efficacy. The empirical findings show that the suggested two-stage model can outperform other competing models in terms of performance.

As a result, a connection between the stock market and AI was established, which produced wonders, to deal with the unstable and dynamic nature of the market. Long Short- Term Memory LSTM, SVM, and ANN were the three techniques used in the prediction process. A neural network is used by ANN, a kernel approach is used by SVM, and Keras LSTM is used by LSTM. It was discovered that ANN based on neural network delivers the greatest results since it takes into account complex, non-linear interactions and recognizes patterns after carefully analyzing the many strategies presented by each methodology (Shah, & Sheth, 2023).

The elements that affect the likelihood of receiving a qualified opinion are examined by the models for predicting audit opinions. This aids auditors in organizing revision processes and managing performance. Existing models only dealt with the larger context for individual financial statements, with no mention of the combined ones, despite their obvious importance. Consolidated data is necessary for decision-making processes and comprehending a company's genuine financial status (Sanchez et al, 2020).

The industry consensus is that ML-based algorithms can be utilized to improve audit efficiency, audit quality, and auditor development. Notably, by combining unsupervised and supervised learning methods, the model for prediction of audit views may successfully address the potential contradiction with the effectiveness of audits and audit risks, boosting the value of listed companies' audit work. While doing so, it can significantly reduce the amount of time spent processing data, eliminate simple duplication of effort, strengthen analysis and monitoring, and enable auditors to address issues using their professional judgments, lowering audit risks and increasing the number of credit conclusions reached to assure the accuracy of audit reports. The early warning of audit risk is another area where machine learning techniques are being used, it can help stakeholders optimize the security market's resource allocation, reduce capital market risk, and maintain market economic order by allowing them to anticipate the types of audit opinions that registered accountants would issue based on relevant information of listed businesses (Zeng et al, 2022).

Based on the above arguments the researchers can conclude the gap between the traditional methods of predicting the stock price and the intelligent methods that depend on machine learning. Thus, the third hypothesis of this research can be developed as follow:

H3: Stock Price is significantly different between the actual value and the predicted using machine learning techniques.

3. Data & Research Methods:

3.1: Data Sampling:

The 758 firm-years observations of Egyptian firms listed on the Egyptian Stock Market between 2012 and 2022 make up the study's data. After removing businesses engaged in the banking and finance industries—businesses where several required characteristics are missing—the sample takes its current form. Following is a breakdown of the sample's distribution by sector and auditor opinion in Table 1:

Table (1): Observations by industries and audit opinion are distributed.

Sector	Unqualified	%	Unqualified with explanatory paragraph	%	Qualified	%	Total	%
Foods	102	16.32	17	17.35	6	17.14	125	16.49
Real Estate	115	18.40	18	18.37	6	17.14	139	18.34
Construction and building materials	117	18.72	18	18.37	7	20.00	142	18.73
Industrials	131	20.96	20	20.41	7	20.00	158	20.84
Basic Resources	65	10.40	10	10.20	4	11.43	79	10.42
Health Care	17	2.72	3	3.06	1	2.86	21	2.77
Energy	5	0.80	1	1.02	0	0.00	6	0.79
Communication & Information Technology	7	1.12	1	1.02	0	0.00	8	1.06
Tourism	66	10.56	10	10.20	4	11.43	80	10.55
Total	***625***	***100***	***98***	***100***	***35***	***100***	***758***	***100***

The table reveals that, out of 625 reports, four industries have gotten the most unqualified audit opinions. These four industries represented in Foods (16.32%), real estate (18.40 %), Construction and building materials (18.72 %), and Industrials (20.96%). The sample reveals that 98 of the observations received unqualified with an explanation other than qualified; the four sectors with the highest percentages recorded are Foods (17.35%), Real Estate (18.37%), Construction and building materials (18.37%), and Industrials (20.41%). Additionally, the table reveals that 35 observations have qualified audit reports. Six industries, including Foods (17.14%), Real Estate (17.14%), Construction and Building Materials (20%), Industrials (20%), Basic Resources (11.43%), and Tourism (11.43%), are where this type of opinion is most frequently expressed.

3.2: Variables Definitions:

The most popular financial indicators in studies that have a bearing on forming an auditor's assessment of the financial statements and forecasting stock price have been utilized to deal with machine learning approaches. The following table provides a summary of these ratios based on the studies mentioned above and the selection of 22 variables as potential indicators of financial statements:

Table (2): The most used financial indicators affecting on auditor opinion and stock price

Variables	Definition	Data Source		
		Financial Statements	Audit Reports	Stock Market
Y1	Dummies assigned the codes 1 for unqualified, 2 for unqualified with justification, and 3 for qualified opinions in the auditor's report.		✓	
Y2	Stock Prices of Listed firms in study sample			✓
X1	Market capitalization is determined by multiplying the number of outstanding shares by the year-end market price.			✓
X2	Current Liabilities subtracted from Current Assets which is equal working capital.	✓		
X3	Using the number of years, a firm has been listed on the stock market, one can estimate its age			✓
X4	Total accruals, which are calculated as the variance between operating cash flow and net income	✓		
X5	A company's total debt is divided by its total assets to determine its debt ratio.	✓		
X6	Cash turnover is calculated by dividing a company's revenues by its average cash balance for the time period.	✓		
X7	Inventory turnover is calculated by dividing a company's revenues by its average inventory over the specified time period.	✓		
X8	Asset intensity, which is determined by dividing the value of all assets by the value of all revenues	✓		

X9	The ratio of total liabilities to total assets, or financial leverage, can be determined.	✓	
X10	Loss, a dummy variable that is coded 1 for loss-making companies and 0 for all other companies	✓	
X11	Return on total assets is determined by dividing an organization's net profit by its total assets.	✓	
X12	Net income is divided by equity to determine a company's return on shareholders' equity.	✓	
X13	EBIT margin is calculated by dividing a company's earnings before interest and tax by its sales.	✓	
X14	Net income/net sales are determined by dividing a company's net income by its net sales for a particular fiscal year.	✓	
X15	Net income: is a company's stated profit or loss for the fiscal year.	✓	
X16	A company's retained earnings are calculated by dividing them by its total assets.	✓	
X17	A company's liquidity ratio is determined by dividing its total cash and cash equivalents by its current obligations.	✓	
X18	Quick ratio: determined by dividing a company's short-term assets by its current liabilities.	✓	
X19	The ratio of receivables to sales is determined by dividing the two.	✓	
X20	Dummy coded 1 for a Big 4 auditor, 0 otherwise, for auditor size.		✓
X21	Natural logarithm of a company's total assets at the conclusion of the fiscal year	✓	
X22	Natural logarithm of a company's net sales for the fiscal year; also known as the log of net sales	✓	

3.3: Research Methods:

This study evaluates how well machine learning methods can forecast audit opinions and stock prices on the Egyptian stock exchange. The Decision Tree (DT), Neural Network (NN), Bayesian Network (BN), Support Vector Machine (SVM), K-Nearest Neighbors (K-NN), Rough Sets (RS), and Random Forest are the most widely used machine learning approaches that deal with financial variables.

Additionally, this study use Probit Regression, a well-known regression technique, to forecast audit opinions and stock prices. The major goal of adopting this traditional approach is to benchmark the differences between the traditional approach and the results anticipated by machine learning techniques. As a result, the following categories can be used to group the machine learning approaches employed in analysis:

3.3.1: Decision tree classification:

A decision tree creates classification or regression models using a tree structure. It segments a dataset into ever-smaller chunks while gradually building an associated decision tree. The result is a tree with decision nodes and leaf nodes (Liangyuan & Lihua, 2022).

The core technique for building decision trees is J. R. Quinlan's ID3, which employs a top-down, greedy search across the area of probable branches without backtracking. Using information gain and entropy, ID3 creates a decision tree. In the ZeroR model, there is no predictor, and in the OneR model, we look for the best predictor we can find. While Bayesian contains all predictors using the Bayes' rule and the independence assumptions between predictors, decision trees contain all predictors with the dependence assumptions between predictors (Liangyuan & Lihua, 2022).

The data are segmented into homogeneous subsets that include instances with comparable values, and a decision tree is built top-down from a root node. The ID3 algorithm uses entropy to assess a sample's homogeneity. If the sample is uniformly distributed, its entropy is one, and if it is completely homogenous, it is zero.

3.3.2: neural networks classification:

Basic electronic neural networks called artificial neural networks are modeled after the brain's neural network. By comparing the known correct classification of each record with their own categorization of the record, which is essentially arbitrary, they process each record individually and learn something. The inaccuracies from the initial categorization of the first record are fed back into the network to enhance the algorithm for subsequent rounds. A neuron in an artificial neural network is (Jospin, et al., 2022):

- a group of weights (w_i) and input values (x_i).

- a formula (g) which adds the weights and converts the output (y) into the desired result.

The three layers that make up a neuron's structure are input, hidden, and output. Instead of complete neurons, the input layer merely consists of the record's values, which are inputs to the subsequent layer of neurons. The next layer is the one that is buried. Multiple hidden layers may exist in a single neural network. One node per class is present in the output layer, which is the final layer. Following a single sweep forward through the network, each output node is assigned a value, and the record is given to the class node with the greatest value (James, et al., 2013).

3.3.3: Bayesian network classification:

The structures of Bayesian networks are mostly unknown. They must therefore be calculated from observed data. Learning Bayesian networks are a method for solving this estimation problem. A score-based technique, which looks for the ideal structure to maximize a score function, is the most popular learning strategy. The marginal probability score is the one that is most frequently used to determine the greatest a posteriori structure. Bayesian Dirichlet equivalence (BDeu) refers to the marginal likelihood (ML) score based on the Dirichlet prior that guarantees likelihood equivalence. The Bayesian Dirichlet equivalence uniform developed by Buntine is frequently applied when there is no prior knowledge. An equivalent sample size (ESS), which is the value of a freely chosen user parameter, is necessary for these scores. Recent investigations have shown that ESS is crucial to the resulting network topology (Jospin, et al., 2022).

3.3.4: Support Vector Machine Classification:

Scikit-Learn's support vector machine supports both dense (numpy.ndarray also adaptable to that numpy.asarray) and sparse (any scipy.sparse) sample vectors as input. However, an SVM must have been fitted on sparse data in order to be used to make predictions for such data. C-ordered data should be used for best results numpy.ndarray (dense) or scipy.sparse.csr_matrix (sparse) with dtype=float64. On a dataset, SVC is qualified to carry out binary and multiple-class classification (James, et al., 2013).

3.3.5: K-Nearest Neighbors classification:

Which category does the new data point, **x1**, belong in if there are two categories, Category A and Category B? A K-NN algorithm is necessary to handle this kind of problem. Finding the category or class of a given dataset is made simple by K-NN. Look at the illustration below (Bremner, et al., 2005):

The following algorithm can be used to describe how the K-NN works:

Step-1: Determine the neighbor's Kth number.

Step-2: Determine the Euclidean distance between K -Neighbors.

Step-3: As determined by the estimated Euclidean distance, select the K closest neighbors.

Step-4: Compute the number of data points in each category among these K -Neighbors.

Step-5: Put the new data points in the category where the neighbor count is at its highest.

Step-6: Our model is ready.

3.3.6: Rough Sets classification:

The induction of (learning) idea approximations is the primary objective of the rough set analysis. Rough sets provide a strong foundation for KDD. It provides analytical techniques for finding patterns in data. It can be used for data reduction, decision rule creation, pattern extraction (templates, association rules), feature selection, feature extraction, and pattern extraction. Identifies data dependencies that are either complete or partial, removes redundant data, and provides solutions for null values, missing data, dynamic data, and other issues. It is a formal approximation of a crisp set whose upper and lower approximations define the set (Herbert & Yao, 2011).

The group of items that could possibly be part of the target set is the upper approximation.

Upper Approximation:

$$\overline{R}X = \bigcup\{Y \in U/R : Y \cap X \neq \phi\}$$

The collection of items that positively belong to the target set is the lower approximation.

Lower Approximation:

$$\underline{R}X = \bigcup\{Y \in U/R : Y \subseteq X\}$$

If a set's boundary area is not empty, it is said to be rough; otherwise, it is said to be crisp.

3.3.7: Random Forest Classification:

We must first examine the ensemble learning method before We can understand how machine learning's random forest algorithm works. Ensemble basically means combining different models. Consequently, the alternative using a only one model to make predictions, a set of models is used (Smith, et al., 2013).

Ensemble employs two different approaches:

A. Bagging: The outcome is decided by a majority vote and using replacement, a separate training subset is produced from a sample of the training data. For illustration, Random Forest.

B. Boosting is a technique for transforming weak learners into strong ones by creating consecutive models as accurately as possible. ADA BOOST and XG BOOST, for instance.

A random forest is a Meta estimator that employs averaging to increase predictive accuracy and reduce over fitting after fitting numerous decision tree classifiers to diverse subsamples of the dataset. The sub-sample size is controlled with the `max_samples` parameter if `bootstrap=True` (default), otherwise the whole dataset is used to build each tree.

The Process of the Random Forest Algorithm:

- **Step 1:** Each decision tree in the Random Forest model is built using a subset of characteristics and a subset of data points. Simply described, the data set containing k records is divided into n random records and m features.
- **Step 2:** Different decision trees are built for every sample.
- **Step 3:** Every decision tree will produce a result.
- **Step 4:** For classification and regression, final results are based on majority voting or averaging, respectively.

4. Analysis of Data & Empirical Results:

4.1: Data Processing:

The majority of datasets contain outliers, which are observations that have unusually high or low values in comparison to the rest of the data and may have an impact on the analysis's findings. The interquartile range (IQR) method is used in this study to find outliers. To help identify whether the dataset contains extreme values, the IQR is calculated as the difference between the third and first quartile of the data. To find and eliminate outliers, the IQR approach uses Q1-1.5 × IQR and Q3 + 1.5 × IQR as the lower and higher bounds, respectively. In other words, a data point is regarded as an outlier if it is either below the lower border or above the upper boundary. Following the application of IQR, a total of 52 outliers were found and eliminated from the research dataset as follows: 43 reports were unqualified, 4 had an explanatory paragraph, and 5 qualified opinions. This table provides a summary of the procedure as follows:

Table (3): The outliers excluding procedure

Sector	Full observations	Outliers	Final observations
Unqualified Opinions	625	43	582
Unqualified with explanatory paragraph Opinions	98	4	94
Qualified Opinions	35	5	30
Total	758	52	706

4.2: Attributes Selection:

The creation of a model using a lot of variables may be hampered by collinearity, which more frequently results in over fitting. Principal components analysis (PCA) is used in this work to minimize dimensionality and overcome the collinearity issue. According on patterns of correlation among the original variables, PCA is a widely used multivariate analytical, statistical technique that condenses a set of independent variables into a smaller set of underlying variables. It is a method for making unsupervised predictions that computes linear combinations of the initial attributes that were created to best explain variation. The PCA's goal is to condense a large set of variables into a manageable number of uncorrelated components that retain the majority of the original variables and suffer the least amount of information loss. A collection of values for variables with no linear correlation make up the main components. The maximum explanatory power is possessed by the first principle component, while the lowest explanatory power is possessed by the last major component. A set of variables with zero correlations are the result of the PCA.

Table (4): Principal Components Loadings

Variables	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
X1	0.0288	0.0741	0.1167	0.0975	0.0990	**0.3746**	0.0260	0.1208	**0.2287**	0.0365	0.0660
X2	0.0772	**0.4258**	0.0599	**0.2077**	0.1176	0.1031	0.0633	0.0373	0.0418	0.0414	0.0378
X3	0.1037	0.0712	**0.3874**	0.1064	0.0635	**0.4638**	0.0322	0.0609	0.0298	0.0718	0.0434
X4	0.0633	0.0358	0.0915	0.0849	0.0852	0.0608	0.0327	**0.3517**	0.0612	**0.4110**	0.1172
X5	0.0884	0.0529	0.0982	0.0427	0.0394	0.0545	**0.3600**	0.0417	0.0604	0.1058	**0.2314**
X6	**0.4349**	0.0472	0.0597	0.0592	**0.3308**	0.0572	0.0841	0.0384	0.0921	0.0893	0.0405
X7	**0.4454**	0.0565	0.0423	0.1067	0.1137	0.0805	0.0678	0.1193	0.0416	**0.3840**	0.1218
X8	0.0644	0.0351	0.0969	0.0800	0.0603	0.1055	**0.2227**	0.0365	**0.3655**	0.0795	0.0794
X9	0.0351	0.1031	0.0773	**0.3887**	**0.4743**	0.0961	0.0926	0.0546	0.0492	0.0289	0.0353
X10	0.1144	**0.3952**	**0.2224**	0.1225	0.0719	0.1025	0.0805	0.1033	0.0238	0.1226	0.0744
X11	**0.4050**	0.0902	0.0280	0.1067	0.1180	**0.3295**	0.0694	0.0600	0.0833	0.1000	0.0597
X12	0.0321	0.1021	0.0652	0.0865	0.0342	0.1083	**0.3956**	0.0242	**0.2316**	0.1097	0.0783
X13	0.0817	**0.2005**	**0.3015**	0.1092	**0.4800**	0.1049	0.0585	0.0784	0.0676	0.0273	0.0270
X14	0.1070	0.0535	0.0351	0.0517	0.0404	0.0251	0.0791	**0.3927**	0.0817	**0.2087**	0.0723
X15	0.0775	0.0892	0.0396	0.0712	0.0342	**0.3635**	0.1136	0.0733	0.0488	0.1029	**0.3406**
X16	0.0696	0.0280	**0.2156**	0.0441	**0.2611**	0.0286	0.0670	0.0909	0.0956	0.0562	0.1201
X17	0.0717	0.1220	0.1185	0.0605	**0.3091**	0.0220	**0.2793**	0.0460	0.0865	0.0388	0.1210
X18	0.1038	**0.4834**	0.0369	0.0465	0.0650	0.0406	0.0337	0.1062	**0.2701**	0.1007	0.0830
X19	0.0891	0.0687	0.0777	**0.4001**	0.0690	0.0623	0.1009	0.1194	0.0933	**0.3740**	0.1017
X20	0.0237	0.0623	**0.3520**	0.0226	0.0891	0.0902	**0.3104**	0.0582	0.0520	0.0862	0.0992
X21	0.0534	**0.2687**	0.0311	0.0334	0.0299	0.0399	0.0419	**0.2061**	0.1013	0.0836	**0.3071**
X22	**0.2973**	0.1212	0.0721	**0.4071**	0.0830	0.1138	0.0652	0.1164	0.0775	**0.3214**	0.1150
Eigenvalue	3.0700	2.8260	2.5350	2.2750	2.2010	2.1700	1.9260	1.9060	1.6740	1.5260	1.0590
Variance explained (%)	0.0846	0.0735	0.0688	0.0684	0.0674	0.0524	0.0522	0.0518	0.0555	0.0337	0.0286
Cum. variance explained (%)	0.0846	0.1581	0.2269	0.2953	0.3627	0.4151	0.4673	0.5191	0.5746	0.6083	0.6369

This study used the PCA to construct 11 additional principle components (attributes), of which 22 were maintained since they had eigenvalues larger than one. These 11 factors account for 63.69% of the total variation in the initial data. The principal component loadings are shown in Table 4 with the coefficient of each original attribute bolded. According to the loadings, the first principal component, for instance, is linked with the variables X6, X7, X11, and X22, or Cash turnover, Inventory turnover, Return on assets, and Log of net sales. Table 4 also contains the bolded coefficients for the other component loadings.

4.3: Correlation Matrix:

The Pearson correlation coefficient (PCC), sometimes referred to as Pearson's r, the Pearson product-moment correlation coefficient (PPMCC), the bivariate correlation, or simply the correlation coefficient in statistics, is a metric for the linear correlation between two sets of data. It is effectively a normalized measurement of the covariance, with the outcome always falling between 1 and 1. It is the ratio of the covariance of two variables to the sum of their standard deviations. Similar to covariance itself, the measure can only account for linear correlation between variables and ignores all other forms of linkages or association. The Pearson's r correlation between the variables' dimensions is shown in Table (5) of the study's findings.

The results included in this table ensure that the correlation coefficients among independent variables are less than 0.8 which mean that there is no multicollinearity among independent variables. Moreover, the independent variables is correlated with dependent variables, which mean that these independent variables are predictable for auditor opinion and stock prices. Finally, the main result of this matrix is the positive relationship between auditor opinion and stock prices, which mean that tending the auditor opinion to be qualified increase the stock price because the auditor opinion gives more confirmation for all external investors about the fairness of financial statements and they are tend to invest in these stocks an raising their demand, consequently the price increase. Based on this result, the first hypothesis of this research can be accepted in the alternative form as follow: ***H1: Audit opinion positively affects the stock price of the company***.

Table (5): Pearson Correlation Matrix

	Y1	Y2	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X22
Y1	1																							
Y2	0.34	1																						
X1	0.24	0.11	1																					
X2	0.25	0.36	0.43	1																				
X3	0.16	0.15	0.06	0.12	1																			
X4	-0.07	-0.19	0.41	0.31	0.14	1																		
X5	-0.19	-0.45	0.09	0.33	0.16	0.41	1																	
X6	0.46	0.34	0.45	0.44	0.27	0.40	0.32	1																
X7	0.41	0.14	0.30	0.09	0.07	0.37	0.35	0.25	1															
X8	0.12	0.34	0.15	0.28	0.18	0.20	0.44	0.22	0.10	1														
X9	-0.06	-0.07	0.35	0.44	0.16	0.24	0.33	0.09	0.25	0.12	1													
X10	-0.39	-0.21	0.29	0.07	0.28	0.40	0.31	0.25	0.41	0.16	0.15	1												
X11	0.13	0.20	0.30	0.13	0.19	0.42	0.12	0.06	0.42	0.24	0.36	0.16	1											
X12	0.43	0.17	0.42	0.36	0.26	0.25	0.44	0.13	0.31	0.08	0.24	0.43	0.06	1										
X13	0.46	0.36	0.15	0.31	0.20	0.37	0.12	0.40	0.44	0.15	0.11	0.43	0.17	0.26	1									
X14	0.11	0.30	0.35	0.27	0.35	0.33	0.31	0.30	0.18	0.11	0.15	0.14	0.21	0.14	0.19	1								
X15	0.41	0.25	0.22	0.22	0.15	0.24	0.18	0.43	0.23	0.09	0.13	0.17	0.42	0.06	0.20	0.29	1							
X16	0.25	0.41	0.39	0.39	0.22	0.10	0.37	0.09	0.19	0.29	0.07	0.25	0.42	0.35	0.21	0.32	0.17	1						
X17	0.20	0.45	0.17	0.22	0.09	0.20	0.35	0.15	0.47	0.29	0.32	0.43	0.36	0.07	0.23	0.06	0.08	0.18	1					
X18	0.34	0.42	0.19	0.14	0.16	0.10	0.44	0.36	0.35	0.09	0.27	0.09	0.09	0.19	0.24	0.34	0.17	0.09	0.10	1				
X19	0.43	0.41	0.20	0.43	0.28	0.10	0.12	0.41	0.34	0.17	0.44	0.20	0.33	0.35	0.34	0.39	0.37	0.17	0.32	0.45	1			
X20	0.30	0.08	0.10	0.43	0.41	0.43	0.43	0.13	0.39	0.10	0.14	0.29	0.22	0.14	0.35	0.18	0.16	0.19	0.35	0.18	0.25	1		
X21	0.43	0.30	0.12	0.44	0.46	0.21	0.16	0.14	0.22	0.46	0.22	0.26	0.43	0.39	0.15	0.46	0.19	0.44	0.10	0.11	0.13	0.25	1	
X22	0.14	0.19	0.21	0.25	0.40	0.29	0.07	0.19	0.23	0.41	0.37	0.39	0.47	0.37	0.31	0.17	0.47	0.32	0.19	0.17	0.46	0.33	0.31	1

4.4: Machine Learning Modeling & Results:

4.4.1: Validation for Modeling:

In order to develop the prediction model utilizing machine learning techniques, this work uses the holdout validation appropriate for machine learning. Specifically, modeling is used using 70% of the data, and of that, 52.5% (or 70% × 75%) are randomly selected as the training dataset for the process of learning the model parameter dataset. The best prediction model is then created using this training dataset, which is continually improved. 17.5% (or 70% 25%) of the data is chosen at random to check the status and convergence of the models during the modeling process, to change the hyper-parameters, to prevent over fitting, and to decide when to finish the training. The rest of data which is equal 30% used as the test dataset to gauge the models' performance (generalization ability). The approach for this investigation was random sampling without replacement. The most important indicators for evaluating the performance quality are accuracy, sensitivity, precision and F1 score, these indicators included in the confusion matrix method.

4.4.2: Decision Tree (DT) results:

To create the optimal model, the crucial variables chosen to predict the auditor opinion are employed in the Decision Tree (DT) model and continually (Training time: 500 microseconds; 150 epochs) trained till stable. The training dataset and validation dataset have accuracy rates of 96.87% and 90.87%, respectively. Additionally, the accuracy rate of the model is tested using the test dataset where the accuracy rate is 89.19%, and the results show the model stability, with the first error type rates of 3.69 % and the second error type rates of 3.5 %, as shown in Table 6 (where, "Unqualified" is predicted when it should be "Unqualified with exp. language" or "Qualified." This is known as the first error type. The second error type: Refers to the mistake of assuming "qualified" or "qualified with exp. language" when it is actually "unqualified."). As shown in Table 6, the confusion matrix indicators for the Decision Tree (DT) model are accuracy = 90.94%, precision = 85.47%, sensitivity (recall) = 84.37%, specificity = 92.20%, and F1-score = 84.92%. These indicators are used in addition to accuracy to assess a model's performance. These metrics show that the model is doing well.

Table (6): Decision Tree (DT) results

Accuracy of the Decision Tree (DT) model							
Model	Dependent Variable	Training Dataset	Validation Dataset	Test Dataset	Average	The first error type	The second error type
Decision Tree (DT)	Auditor Opinion (Y1)	96.87%	90.87%	89.19%	92.31 %	3.69%	3.53%

	Stock Price (Y2)	92.75%	87.03%	89.10%	89.63 %	2.96%	2.91%
Confusion matrix indicators: Decision Tree (DT)							
Model	Dependent Variable	Accuracy	Precision	Sensitivity (Recall	Specificity	F1 Score	Training Time
Decision Tree (DT)	Auditor Opinion (Y1)	90.94%	85.47%	84.37%	94.20 %	84.92%	500 µs
	Stock Price (Y2)	91.04%	85.76%	80.95%	96.18 %	83.29%	500 µs

On the other hand, the chosen variables are continually (Training time: 500 microseconds; 150 epochs) trained till stable using the Decision Tree (DT) model for predicting the stock price The training dataset and validation dataset have accuracy rates of 92.75% and 87.03%, respectively. Additionally, the accuracy rate of the model is tested on the test dataset to determine its stability. An accuracy rate differs significantly from the findings of the training and validation datasets where it is equal 89.10% and indicates highly model stability (where, the first error type: Refers to the error of ‘‘increase the price’’ when it is an ‘‘decrease the price’’ & the second error type: Refers to the error of ‘‘decrease the price’’ when it is an ‘‘increase the price’’). As shown in Table 6, the confusion matrix indicators of the Decision Tree (DT) model are accuracy = 91.04%, precision = 85.76%, sensitivity (recall) = 80.95%, specificity = 96.18%, and F1-score = 83.29%. These indicators are used in addition to accuracy to assess a model's performance. These metrics show that the model is doing well.

4.4.3: Neural Networks (NN) results:

In order to build the optimal model, the key variables chosen to predict the auditor opinion are employed in a Neural Networks (NN) model and periodically (Training time: 500 microseconds; 150 epochs) trained till stable. The training dataset and validation dataset have accuracy rates of 95.37% and 91%, respectively. Additionally, the model's stability is tested using the test dataset, which yields an accuracy rate of 89.94%, It indicates that the model is pretty stable and is just a little bit higher than the findings from the training dataset and validation dataset. The first error type rate (3.74%) and the second error type rate (6.09%), (where, "Unqualified" is predicted when it should be "Unqualified with exp. language" or "Qualified." This is known as a The first error type. The second error type: Refers to the mistake of assuming "qualified" or "qualified with exp. language" when it is actually "unqualified."). as shown in Table 7, also indicate that the model is quite stable. In the context of model stability, the included indicators in the Neural Networks (NN) confusion matrix revealed the high stability where accuracy = 90.13%, precision = 87.18%, sensitivity (recall) = 76.22%, specificity = 95.67%, and F1-score = 81.33%.

On the other hand, the chosen variables are continually trained until stable using a Neural Networks (NN) model for predicting the stock price (training time: 500 microseconds; 150 epochs). The training dataset and validation dataset have accuracy rates of 96.66% and 88.03%, respectively. Additionally, the accuracy rate of 86.50%, this shows that the model is highly stable and which differs only minimally from the findings of the training dataset and validation dataset. The first error type rate (3.42%) and the second error type rate (3.44%), (where, the first error type: Refers to the error of ‘‘increase the price’’ when it is an ‘‘decrease the price’’ & The second error type: Refers to the error of ‘‘decrease the price’’ when it is an ‘‘increase the price’’), as shown in Table 7, also indicate that the model is quite stable. In addition, the confusion matrix indicators which are shown in table 7 ensure that the model is highly doing well where accuracy = 92.10%, precision = 87.95%, sensitivity (recall) = 79.96%, specificity = 95.23%, and F1-score = 83.76%.

Table (7): Neural Networks (NN) results

Accuracy of the Neural Networks NN model							
Model	Dependent Variable	Training Dataset	Validation Dataset	Test Dataset	Average	The first error type	The second error type
Neural Networks (NN)	Auditor Opinion (Y1)	95.37%	91.00%	89.94%	92.10 %	3.74%	6.09%
	Stock Price (Y2)	96.66%	88.03%	86.50%	90.40 %	3.42%	3.44%
Confusion matrix indicators: Neural Networks (NN)							
Model	Dependent Variable	Accuracy	Precision	Sensitivity (Recall	Specificity	F1 Score	Training Time
Neural Networks (NN)	Auditor Opinion (Y1)	90.13%	87.18%	76.22%	95.67 %	81.33%	500 µs
	Stock Price (Y2)	92.10%	87.95%	79.96%	95.23 %	83.76%	500 µs

4.4.4: Bayesian Networks (BN) results:

In order to build the optimal model, the key variables chosen to predict the auditor opinion are employed in the Bayesian Networks (BN) model and periodically (Training time: 500 microseconds; 150 epochs) trained till stable. The training dataset and validation dataset have accuracy rates of 96.13% and 89.57%, respectively. Additionally, the accuracy rate of 90.16% obtained from the test dataset—which is differ significantly than the results of the training dataset and validation dataset—is used to test the model's stability. The first error type rate (2.42%) and the second error type rate (3.12%), (where, "Unqualified" is predicted when it should be "Unqualified with exp. language" or "Qualified." This is known as the first error type. The second error type: Refers to the mistake of assuming "qualified" or "qualified with exp. language" when it is actually "unqualified."), as shown in Table 8—indicate that the model is quite stable. Moreover, the Bayesian Networks (BN) confusion matrix indicators ensure highly performance of this model because of accuracy = 91.16%, precision = 89.26%, sensitivity (recall) =

75.72%, specificity = 94.98%, and F1-score = 81.93%. These indicators are used in addition to accuracy to assess a model's performance. These metrics show that the model is doing well.

On the other hand, the chosen variables are continually trained until stable using the Bayesian Networks (BN) model for predicting the stock price (training time: 500 microseconds; 150 epochs). The training dataset and validation dataset have accuracy rates of 92.22% and 86.67%, respectively. Additionally, the accuracy rate of 85.25%, thus, while being little unique from the results of the training and validation datasets, ensures that the model is highly stable. The first error type rate (3.77%) and the second error type rate (2.20%), (where, the first error type: Refers to the error of ‘‘increase the price’’ when it is an ‘‘decrease the price’’ & the second error type: refers to the error of ‘‘decrease the price’’ when it is an ‘‘increase the price’’), as shown in Table 8, also indicate that the model is quite stable. The confusion matrix indicators, as displayed in Table 8, for the Bayesian Networks (BN) model are accuracy = 91.20%, precision = 87.36%, sensitivity (recall) = 82.05%, specificity = 96.85%, and F1-score = 84.62%. These indicators are used in addition to accuracy to assess a model's performance. These metrics show that the model is doing well.

Table (8): Bayesian Networks (BN) results

Accuracy of the Bayesian Networks (BN) model							
Model	Dependent Variable	Training Dataset	Validation Dataset	Test Dataset	Average	The first error type	The second error type
Bayesian Networks (BN)	Auditor Opinion (Y1)	96.13%	89.57%	90.16%	91.95 %	2.42%	3.12%
	Stock Price (Y2)	92.22%	86.67%	85.25%	88.05 %	3.77%	2.20%
Confusion matrix indicators: Bayesian Networks (BN)							
Model	Dependent Variable	Accuracy	Precision	Sensitivity (Recall	Specificity	F1 Score	Training Time
Bayesian Networks (BN)	Auditor Opinion (Y1)	91.16%	89.26%	75.72%	94.98 %	81.93%	500 µs
	Stock Price (Y2)	91.20%	87.36%	82.05%	96.85 %	84.62%	500 µs

4.4.5: Support Vector Machine (SVM) results:

To create the best model, the crucial variables chosen to predict the auditor opinion are employed in the Support Vector Machine (SVM) model and continually (Training time: 500 microseconds; 150 epochs) trained till stable. The training dataset and validation dataset have accuracy rates of 95.24% and 90.90%, respectively. Additionally, the accuracy rate of 90.60%, this shows that the model is highly stable and which differs only minimally from the findings of the training and validation datasets. The first error type rate (3.73%) and the second error type rate (2.45%), (where, "Unqualified" is predicted when it should be "Unqualified with exp. language" or "Qualified." This is known as the first error type. The second error type: refers to the mistake of assuming "qualified" or "qualified with exp. language" when it is actually "unqualified."), as shown in Table 9, also indicate that the model is quite stable. The confusion matrix indications for the Support Vector Machine (SVM) model are displayed in Table 9 are accuracy = 91.49%, precision = 86.25%, sensitivity (recall) = 84.18%, specificity = 94.29%, and F1-score = 85.20%. These indicators are used in addition to accuracy to assess a model's performance. These metrics show that the model is doing well.

On the other hand, the chosen variables are periodically (Training time: 500 microseconds; 150 epochs) trained till stable using the Support Vector Machine (SVM) model for predicting the stock price. The training dataset and validation dataset have accuracy rates of 93.44% and 87.84%, respectively. Additionally, the accuracy rate of 88.56% obtained from the test dataset, this shows that the model is highly stable and which differs only minimally from the findings of the training and validation datasets. The first error type rate (2.50%) and The second error type rate 6.25%, where, the first error type: Refers to the error of ‘‘increase the price’’ when it is an ‘‘decrease the price’’ & the second error type: refers to the error of ‘‘decrease the price’’ when it is an ‘‘increase the price’’), as shown in Table 9, also indicate that the model is stable. The confusion matrix indications for the Support Vector Machine (SVM) model are displayed in Table 9 are accuracy = 91.14%, precision = 85.23%, sensitivity (recall) = 83.45%, specificity = 94.99%, and F1-score = 84.33%. These indicators are used in addition to accuracy to assess a model's performance. These metrics show that the model is doing well.

Table (9): Support Vector Machine (SVM) results

Accuracy of the Support Vector Machine (SVM) model							
Model	Dependent Variable	Training Dataset	Validation Dataset	Test Dataset	Average	The first error type	The second error type
Support Vector Machine (SVM)	Auditor Opinion (Y1)	95.24%	90.90%	90.60%	92.25 %	3.73%	2.45%
	Stock Price (Y2)	93.44%	87.84%	88.56%	89.95 %	2.50%	6.25%
Confusion matrix indicators: Support Vector Machine (SVM)							
Model	Dependent Variable	Accuracy	Precision	Sensitivity (Recall	Specificity	F1 Score	Training Time
Support Vector Machine (SVM)	Auditor Opinion (Y1)	91.49%	86.25%	84.18%	94.29 %	85.20%	500 μs
	Stock Price (Y2)	91.14%	85.23%	83.45%	94.99 %	84.33%	500 μs

4.4.6: K-Nearest Neighbors (K-NN) results:

The best model is built by periodically training the K-Nearest Neighbors (K-NN) model trained till stable (Training time: 500 microseconds; 150 epochs) using the significant variables chosen to predict the auditor opinion. The training dataset and validation dataset have accuracy rates of 95.03% and 90.68%, respectively. Additionally, the accuracy rate on the test dataset, is somewhat greater than the results of the training and validation datasets, shows the model stability, with the first error type rate of 6.12% and the second error type rate of 6.10 percent, (where, "Unqualified" is predicted when it should be "Unqualified with exp. language" or "Qualified." This is known as the first error type. The second error type: Refers to the mistake of assuming "qualified" or "qualified with exp. language" when it is actually "unqualified.") As shown in Table 10. Moreover, the confusion matrix indicators which are used in assessing the model's performance proved that the model is doing well where accuracy = 92.15%, precision = 88.82%, sensitivity (recall) = 86.46%, specificity = 96.93%, and F1-score = 87.62%.

On the other hand, the chosen variables are regularly (Training time: 500 microseconds; 150 epochs) trained till stable using the K-Nearest Neighbors (K-NN) model for predicting the stock price. The training dataset and validation dataset have accuracy rates of 92.46% and 88.14%, respectively. Additionally, the accuracy rate of 87.37%, thus, while being is somewhat greater than the results of the training and validation datasets, shows the model is highly model stability. The first error type rate (3.64%) and the second error type rate (2.79%), (where, the first error type: refers to the error of ‘‘increase the price’’ when it is an ‘‘decrease the price’’ & the second error type : refers to the error of ‘‘decrease the price’’ when it is an ‘‘increase the price’’), as shown in Table 10, also indicate that the model is quite stable. The confusion matrix indications for the K-Nearest Neighbors (K-NN) model are displayed in Table 10 are accuracy = 92.23%, precision = 85.48%, sensitivity (recall) = 78.51%, specificity = 94.28%, and F1-score = 81.85%. These indicators are used in addition to accuracy to assess a model's performance. These metrics show that the model is doing well.

Table (10): K-Nearest neighbours (K-NN) results

Accuracy of the K-Nearest neighbours (K-NN) model							
Model	Dependent Variable	Training Dataset	Validation Dataset	Test Dataset	Average	The first error type	The second error type
K-Nearest neighbours (K-NN)	Auditor Opinion (Y1)	95.03%	90.68%	90.44%	92.05 %	6.12%	6.10%
	Stock Price (Y2)	92.46%	88.14%	87.37%	89.32 %	3.64%	2.79%
Confusion matrix indicators: K-Nearest Neighbours (K-NN) model							

Model	Dependent Variable	Accuracy	Precision	Sensitivity (Recall	Specificity	F1 Score	Training Time
K-Nearest neighbours (K-NN)	Auditor Opinion (Y1)	92.15%	88.82%	86.46%	96.93 %	87.62%	500 µs
	Stock Price (Y2)	92.23%	85.48%	78.51%	94.28 %	81.85%	500 µs

4.4.7: Rough Sets (RS) results:

The important variables selected to predict the auditor opinion are used for Rough Sets (RS) model and repeatedly (Training time: 500 microseconds; 150 epochs) trained till stable, to build the finest possible model. The training dataset and validation dataset have accuracy rates of 94.99% and 90.74%, respectively. Additionally, the accuracy rate of 90.94% obtained from the test dataset, which is significantly dissimilar training and validation datasets results, and prove the highly stability of the model. The first error type rate (4.99%) and the second error type rate (2.58%), as shown in Table 11, also indicate that the model is quite stable (where, "Unqualified" is predicted when it should be "Unqualified with exp. language" or "Qualified." This is known as a first error type. The second error type: Refers to the mistake of assuming "qualified" or "qualified with exp. language" when it is actually "unqualified."). As shown in Table 11, the confusion matrix indicators for the Rough Sets (RS) model are accuracy = 91.41%, precision = 88.21%, sensitivity (recall) = 87.72%, specificity = 97.26%, and F1-score = 87.96%. These indicators are used in addition to accuracy to assess a model's performance. These metrics show that the model is doing well.

On the other side, the selected variables for predicting the stock price using Rough Sets (RS) model are repeatedly (Training time: 500 microseconds; 150 epochs) trained till stable. The training dataset and validation dataset have accuracy rates of 96.24% and 87.44%, respectively. Additionally, the accuracy rate of 87.58%, which is dissimilar from the results of the training and validation datasets, proves that the model is stable to some extent. The first error type rate (4.36%) and the second error type rate (4.77%), as shown in table 11, also ensure the model stability, (where, the first error type: refers to the error of ‘‘increase the price’’ when it is an ‘‘decrease the price’’ & The second error type: Refers to the error of ‘‘decrease the price’’ when it is an ‘‘increase the price’’). As shown in Table 11, the indicators of confusion matrix to the Rough Sets (RS) model are accuracy = 90.70%, precision = 87.93%, sensitivity (recall) = 78.84%, specificity = 94.18%, and F1-score = 83.14%. These indicators are used in addition to accuracy to assess a model's performance. These metrics show that the model is doing well.

Table (11): Rough Sets (RS) results

Accuracy of the Rough Sets (RS) model							
Model	Dependent Variable	Training Dataset	Validation Dataset	Test Dataset	Average	The first error type	The second error type
Rough Sets (RS)	Auditor Opinion (Y1)	94.99%	90.74%	90.94%	92.22 %	4.99%	2.58%
	Stock Price (Y2)	96.24%	87.44%	87.58%	90.42 %	4.36%	4.77%
Confusion matrix indicators: Rough Sets (RS)							
Model	Dependent Variable	Accuracy	Precision	Sensitivity (Recall	Specificity	F1 Score	Training Time
Rough Sets (RS)	Auditor Opinion (Y1)	91.41%	88.21%	87.72%	97.26 %	87.96%	500 µs
	Stock Price (Y2)	90.70%	87.93%	78.84%	94.18 %	83.14%	500 µs

4.4.8: Random Forest (RF) results:

The important variables selected to predict the auditor opinion are used for Random Forest (RF) model and repeatedly (Training time: 500 microseconds; 150 epochs) trained till stable, to build the finest possible model. The training dataset and validation dataset have accuracy rates of 94.56% and 89.39%, respectively. Additionally, the accuracy rate of 91% obtained from the test dataset, which differs slightly from the training and validation datasets results, proves the highly stability of the model. The first error type rate (2.93%) and the second error type rate (5.21%), as shown in Table 12, also indicate that the model is quite stable (where, "Unqualified" is predicted when it should be "Unqualified with exp. language" or "Qualified." This is known as the first error type. The second error type: Refers to the mistake of assuming "qualified" or "qualified with exp. language" when it is actually "unqualified."). As shown in Table 12, the indicators confusion matrix that related to running the Random Forest (RF) model are accuracy = 90.80%, precision = 87.94%, sensitivity (recall) = 85.15%, specificity = 95.11%, and F1-score = 86.52%. These indicators are used in addition to accuracy to assess a model's performance. These metrics show that the model is doing well.

On the other side, the selected variables for predicting the stock price using Random Forest (RF) model are repeatedly (Training time: 500 microseconds; 150 epochs) trained till stable. The training dataset and validation dataset have accuracy rates of 93.25% and 88.33%, respectively. Additionally, the accuracy rate of the model is tested on the test dataset to determine its stability. An accuracy rate of 88.79% is obtained, which differs slightly from the results of the training dataset and validation dataset and shows that the model is quite stable, (where, the first error type: Refers to the error of ‘‘increase the price’’ when it is an ‘‘decrease the price’’ & the second error type: Refers to the error of ‘‘decrease the price'' when it is an ''increase the price''). As shown in Table 12, the indicators of confusion matrix related to the Random Forest (RF) model are accuracy = 91.32%, precision = 85.20%, sensitivity (recall) = 83.98%, specificity = 95.27%, and F1-score = 84.59%. These indicators are used in addition to accuracy to assess a model's performance. These metrics show that the model is doing well.

Table (12): Random Forest (RF) results

Accuracy of the Random Forest RF model							
Model	Dependent Variable	Training Dataset	Validation Dataset	Test Dataset	Average	The first error type	The second error type
Random Forest (RF)	Auditor Opinion (Y1)	94.56%	89.39%	91.00 %	91.65%	2.93%	5.21%
	Stock Price (Y2)	93.25%	88.33%	88.79 %	90.12%	4.09%	3.16%
Confusion matrix indicators: Random Forest (RF)							
Model	**Dependent Variable**	**Accuracy**	**Precision**	**Sensitivity (Recall**	**Specificity**	**F1 Score**	**Training Time**
Random Forest (RF)	Auditor Opinion (Y1)	90.80%	87.94%	85.15 %	95.11%	86.52%	500 µs
	Stock Price (Y2)	91.32%	85.20%	83.98 %	95.27%	84.59%	500 µs

4.5: Traditional Modeling & Testing Difference:

The results of using the indicators of auditor opinion and stock prices using probit regression can be showed in table (13) as follow:

Table (13): Probit Regression results

Parameter	**Dependent Variable: Auditor Opinion**				**Dependent Variable: Stock Price**			
	Estimate	**Std. Error**	**Z**	**Sig.**	**Estimate**	**Std. Error**	**Z**	**Sig.**
X1	0.445	0.120	0.558	0.088	0.498	0.107	0.961	0.117
X2	**0.371**	**0.108**	**3.360**	**0.001**	0.419	0.112	0.505	0.067
X3	0.486	0.109	0.479	0.120	**0.314**	**0.108**	**2.555**	**0.039**
X4	0.310	0.079	0.737	0.108	**0.424**	**0.097**	**2.807**	**0.030**
X5	**0.452**	**0.082**	**2.562**	**0.044**	0.420	0.091	0.589	0.068
X6	0.510	0.115	0.557	0.121	0.452	0.104	0.459	0.080
X7	**0.312**	**0.103**	**2.446**	**0.021**	**0.456**	**0.079**	**3.836**	**0.008**
X8	0.533	0.106	1.317	0.082	0.323	0.100	1.153	0.089

X9	0.401	0.105	0.796	0.080	0.567	0.117	1.090	0.116
X10	0.551	0.099	0.625	0.073	0.340	0.112	1.388	0.099
X11	0.477	0.087	0.395	0.112	0.535	0.115	0.519	0.101
X12	0.414	0.087	1.652	0.093	**0.360**	**0.125**	**3.146**	**0.002**
X13	**0.353**	**0.100**	**2.986**	**0.034**	0.437	0.088	0.365	0.069
X14	**0.501**	**0.123**	**3.489**	**0.043**	**0.258**	**0.095**	**3.269**	**0.008**
X15	**0.448**	**0.100**	**3.163**	**0.037**	**0.394**	**0.096**	**3.651**	**0.014**
X16	0.340	0.093	0.916	0.063	**0.483**	**0.116**	**2.572**	**0.045**
X17	0.304	0.111	1.613	0.074	0.543	0.104	1.670	0.105
X18	0.441	0.094	0.963	0.051	**0.275**	**0.101**	**3.449**	**0.047**
X19	**0.256**	**0.078**	**3.110**	**0.014**	0.538	0.107	0.783	0.114
X20	0.317	0.116	1.554	0.106	0.345	0.101	1.337	0.050
X21	**0.332**	**0.102**	**2.883**	**0.045**	**0.270**	**0.096**	**3.667**	**0.037**
X22	0.293	0.119	0.744	0.056	0.409	0.099	1.367	0.102
Intercept	**0.521**	**0.118**	**2.013**	**0.023**	**0.400**	**0.101**	**2.301**	**0.002**
Optimal Solution Found	***Yes***				***Yes***			
N	***706***				***706***			
Chi-Square	***526.411***				***326.218***			
Sig.	***0.325***				***0.211***			

The optimal solutions for the both models are found, and the Chi-Square for the both models are also insignificant which means that the model is good fit. It is obvious that the both models did not use all indicators, where there are a number of variables is not significant which is mean decreasing the accuracy of the traditional models in predicting.

Based on these results, the comparison between the predicted values and actual values must be done in the following section as follow:

4.5.1: Auditor opinion comparisons:

Based on the above results, the machine learning techniques are outperformed the traditional methods. Consequently, we conclude some comparisons between the actual opinion and predicted opinion as follow:

Table (14): Compared means between actual and predicted results of auditor opinion

	Variables	Mean	T	Sig. (2-tailed)
Pair (1)	Actual Audit opinion	1.222	4.681	0.000
	Predicted Audit opinion using ML	1.111		
Pair (2)	Actual Audit opinion	1.222	-7.404	0.000
	Predicted Audit opinion using Traditional methods	1.410		
Pair (3)	Predicted Audit opinion using ML	1.111	-8.451	0.000
	Predicted Audit opinion using Traditional methods	1.410		

The results of comparing the means of the actual audit opinion and the predicted audit opinion using machine learning are presented in pair (1) in Table

14. These results show that the actual audit opinion is biased toward the "qualified" or "unqualified with exp. language" opinion, where the difference is significant, because of the high accuracy of machine learning technology. As a result, we draw the conclusion that actual audit opinions and machine-learning-predicted audit opinions (also known as biased actual audit opinions) differ significantly.

In pair (2), the results of comparing the means of the actual audit opinion and the predicted audit opinion using traditional methods show that the means of the predicted are greater than those of the actual, indicating that the former is biased toward the "unqualified with exp. language" or "qualified" opinion, where the difference is significant, as a result of the low accuracy of traditional methods. As a result, we draw the conclusion that actual audit opinions and predicted audit opinions based on traditional methods (biased predicted audit opinions based on traditional methods) differ significantly.

The results of pair (3) show that the means of the predicted audit opinions using traditional methods are greater than those of the predicted audit opinions using machine learning. This means that the predicted audit opinions using traditional methods are biased toward the "unqualified with exp. language" or "qualified" opinion, where the difference between the two is the amount of predictive accuracy. As a result, we draw the conclusion that the predicted audit opinion based on machine learning techniques and the predicted audit opinion based on traditional methods (biased predicted audit opinion based on traditional methods) differ significantly.

Finally, based on the above results we can accept the second hypothesis on the alternative form as follow: ***H2: Audit opinion is significantly different between the actual value and the predicted using machine learning techniques.***

4.5.2: Stock Price comparisons:

Based on the above results, the machine learning techniques (i.e., SVM and Naïve Bayes) is outperformed the traditional methods (i.e., logistic and prrobit regressions). Consequently, we conclude some comparisons between the actual price and predicted price as follow:

Table (15): Compared means between actual and predicted results of stock price

	Variables	Mean	T	Sig. (2-tailed)
Pair (1)	Actual Δ stock price	0.065	2.411	0.000
	Predicted Δ stock price	.087		

The results of comparing the means of the actual stock price and the predicted stock price using machine learning are presented in pair (1) in Table 15. These results show that the means of the actual stock price are biased toward "declining the price," where the difference is significant, due to the high accuracy of machine learning techniques. As a result, we can accept the third hypothesis on the alternate form, which can be as follows: ***H3: Stock Price is significantly different between the actual value and the predicted using machine learning techniques.***

5. Conclusion and Future Research

The research aims to Predict the auditor opinion and stock price by using Machine Learning Techniques , deals with the predicting errors of the auditor opinions and the stock prices, tries to identify the significant differences among the predicted values of the auditor opinions and the stock prices and the actual values, and makes an effort to close the gap by dividing the audit findings into multiple categories, namely qualified using a very limited dataset, qualified using explanatory language, and unqualified.

The DT, NN, BN, SVM, K-NN, RS, and random forest are the most widely used machine learning approaches that deal with financial variables. Additionally, this study use Probit Regression, a well-known regression technique, to forecast audit opinions and stock prices. The major goal of adopting this traditional approach is to benchmark the differences between the traditional approach and the results anticipated by machine learning techniques.

The 758 firm-years of Egyptian firms listed on the Egyptian stock exchange from 2012 to 2022 make up the data for this study. After eliminating businesses engaged in the banking and financial sectors and businesses with a large number of missing data from the sample forms.

The results revealed that positive relationship between auditor opinion and stock prices, which mean that tending the auditor opinion to be qualified increase the stock price because the auditor opinion give more confirmation for all external investors about the fairness of financial statements and they are tend to invest in these stocks raising their demand, consequently the price increase. So, the first hypothesis of this research can be accepted, Audit opinion positively affects the stock price of the company.

The results show that the means of the predicted audit opinions using traditional methods are greater than those of the predicted audit opinions using machine learning. This means that the predicted audit opinions using traditional methods are biased toward the "unqualified with exp. language" or "qualified" opinion, where the difference between the two is the amount of predictive accuracy. We can accept the second hypothesis; audit opinion is significantly different between the actual value and the predicted using ML techniques.

The results indicate that the means of predicted stock price using ML higher than actual stock price which means that actual stock price biased toward the ‘‘decrease the price, where the difference is significant, because of the high accuracy of ML techniques. So can accept the third hypothesis, stock price is significantly different between the actual value and the predicted using machine learning techniques.

The researcher recommends measuring the impact machine learning algorithms and continuous auditing, audit quality, and internal auditing in the Egyptian environment.

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