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The Impact of Balanced Scorecard on Improving the Accuracy of Compliance Audit Predictions Through the Use of Machine Learning Techniques

Mozamil A. Taha

Accounting Department, Faculty of Business Administration, Taif University, Taif, Saudi Arabia
Email: malhadad@tu.edu.sa

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Abstract

Compliance audits play a crucial role in ensuring organizations adhere to regulatory requirements and internal policies. Accurate predictions of compliance audit outcomes can help organizations proactively address compliance issues and enhance overall performance. This study explores the application of machine learning techniques to predict compliance audit results and introduces the Balanced Scorecard as an independent variable to improve prediction accuracy. The research leverages historical audit data, encompassing audit findings, violations, and various organizational attributes. Machine learning models are trained to forecast the likelihood of non-compliance events, while also incorporating the Balanced Scorecard metrics as an independent variable. The Balanced Scorecard framework offers a comprehensive analysis of the performance of a company, encompassing financial, customer, Internal operations, and learning and growth perspectives. By integrating the Balanced Scorecard metrics into the predictive models, this study aims to assess the impact of strategic and operational performance on compliance audit outcomes. Preliminary findings suggest that the inclusion of Balanced Scorecard data enhances the predictive capabilities of machine learning models, enabling organizations to identify compliance risks aligned with their strategic objectives. The implications of this research are significant, offering organizations a proactive approach to compliance management. The ability to anticipate compliance issues through machine learning-driven predictions, coupled with insights from the Balanced Scorecard, empowers decision-makers to allocate resources strategically and align compliance efforts with broader organizational goals. This study provides valuable insights into the synergy between compliance audit prediction, machine learning, and the Balanced Scorecard, offering a promising avenue for organizations to enhance their compliance management strategies and overall performance.

Keywords

Balanced Scorecard, Compliance Audit, Machine Learning Techniques, Predictive

1. Introduction

The Balanced Scorecard is a successful model for efficient reporting on compliance, with its primary goal of providing openness for all compliance, its emphasis on strategic alignment, and its wide viewpoint that goes beyond financial metrics efforts (Wijaya, 2024). The Business and Professional Accountants (PAIB) The International Federation of Accountants (IFAC) Committee (2004) declares that a business needs to figure out how to strike the ideal balance between conformity. They are two crucial aspects of adherence. To keep an eye on performance, the Management Accountants Chartered Institute (CIMA) recommends using a strategy scorecard to guarantee compliance. The use of the scorecard is also on the compliance side supporting governance and compliance where the scorecard identifies the overall value of corporate governance (Strenger, 2004). It can also provide a basis for corporate monitoring (Mäder, 2006).

The existing infrastructure should be utilized to prepare regular reports for the company's compliance management (Goeken & Knackstedt, 2008). This must be measured accurately the reason being that "If you can't measure it, you can't manage it", as stated by Kaplan and Norton (Kaplan & Norton, 1997). A widely used tool in preparing regular reports is the balanced scorecard, through which centralized information presentation can be ensured(Horváth, 2007). Its use also helps in finding commonalities. Its growing usage may also be expected in the field of soon to come: governance and compliance (Horváth & De Haes, 2005). Compliance scorecards are very popular, because it highlights the significance of compliance, encourages the creation of a compliance strategy, and visualizes causal relationship relationships. By pooling compliance functions, it brings about the transparency needed to find areas of overlap, get rid of obstacles, and demonstrate to auditors that compliance measures work (Panitz et al., 2010). Machine learning has a positive impact on increasing a company's production capacity, customer retention, and growth in light of the rapid technological advancement we are witnessing today. Machine learning algorithms are therefore seen as an instrument that can help in more effectively handling a range of potential problems in a business by accelerating examination and increasing production (Tagkouta et al., 2023).

The analysis conducted focuses on examining the impact of the balanced scorecard on commitment. In addition, it seeks to identify the critical dimensions that must be considered when designing compliance reports, i.e. those that have an impact on them. This brings us to the most important the following are the main research questions: Does the inclusion of balanced scorecard dimensions enhance the predictive capabilities of machine learning models and does balanced scorecard insights improve compliance audit efforts? This study aimed to fill the gap in the literature about the correct prediction of compliance reports using machine learning models, which was not previously explored.

The main objective of this study is to create prediction models that can accurately predict the outcomes of compliance audits with exceptional accuracy and to illustrate the role of the balanced scorecard in enhancing the predictive capabilities of machine learning models. This study seeks to assess the influence of strategic and operational performance on compliance audit results. Initial findings suggest that integrating balanced scorecard data improves the predictive efficacy of machine learning models, allowing organisations to detect compliance risks aligned with their strategic goals. This research has substantial ramifications, providing organisations with a proactive strategy for compliance management. The capacity to foresee compliance challenges using machine learning predictions, along with insights from the balanced scorecard, empowers decision-makers to strategically distribute resources and connect compliance initiatives with overarching organisational objectives. This work offers significant insights into the interplay between compliance audit prediction, machine learning, and the balanced scorecard, presenting a promising avenue for organisations to improve their compliance management strategies and overall performance.

This paper is organized as follows: the introduction and subsequent sections in particular. Section 2 provides a comprehensive explanation of the research methodology used in the study, with a strong focus on networks, decision trees, and the mathematical formulas used to calculate the statistical measures used in the model comparison. In Section 3 of the paper, we provide basic definitions of the study variables and those related to the concept-based hypotheses. Section 4 then presents the results obtained, while Section 5 provides an expanded analysis and interpretation of these results. In short, the above points, taken together, provide evidence that supports the research objective.

2. Methodology

2.1. Sampling and Data Generation

Expert consultations are particularly appropriate when conducting qualitative research, if the subject of study is not the same in all its dimensions as in previous studies. This approach was chosen for data collection due to the fact that compliance reporting has not been discussed in more detail to date. Interviews typically capture the opinions of experts with superior knowledge of the subject of compliance reporting resulting from their role within the organization. Therefore, in contrast to in-person interviews, the researcher is more interested in the respondents' roles as subject matter experts than in the interviewees themselves. knowledge bases, relevance structures, and socially held interpretations and constructions of reality are all implied in addition to the knowledge of a single individual. Theories are developed based on the information gathered from the interviews. The initial systematic theory discovery from the data is stated as the best way to be reasonably assured that the theory would fit and function. For this reason, the data were assessed using the grounded theory method. Its foundation is the methodical creation of hypothesis from data that is methodically gathered from social science research. Consequently, the grounded theory approach offers a methodical, exacting manual for developing theories. This approach of qualitative research aims to construct theories based on factual information. The goal of the theory is to identify the higher social structures that are responsible for the construction and reconstruction of pertinent conceptions as well as to illuminate the significance of human experiences. Grounded theory methodology is used to develop theories that are pertinent to the compliance reporting study issue (Panitz et al., 2010). This study focuses on the insurance sector in Sudanese companies listed on the Khartoum Stock Exchange until 31 December 2022.

2.2. Data Collection

To conduct the expert interviews, a questionnaire was developed based on the research background to ensure that all topics relevant to the research area were addressed. As a subsequent measure, a pre-test was conducted to check the survey for suitability, and the questionnaire form was revised during a practical interview with an expert. The questionnaires were also revised to ensure ease of understanding and additional topics identified as important were added.

Since they are in charge of confirming compliance and are knowledgeable about compliance standards, 53 questionnaires were given to the study sample, which consists of internal audit managers and internal auditors in the companies under investigation. After completing the questionnaire, forty of them returned it.

2.3. Precision Measurement

To evaluate the accuracy of the prediction, the researcher used four statistical measures: mean square error (MSE) and root mean square error (RMSE), symmetric mean absolute percentage error (SMAPE), mean absolute percentage error (MAPE) (Reda Abonazel, 2018). The formulas for MSE, RMSE, SMAPE, and MAPE are as follows (Torsen et al., 2018).

$$\text{Mean square error } (MSE) = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{1}$$

$$\text{Root Mean square error } (RMSE) = \sqrt{MSE} \tag{2}$$

$$\text{Symmetric Mean Absolute Percentage Error } (SMAPE) = \frac{1}{N}\sum_{i=1}^{n}\frac{\left|y_i - \hat{y}_i\right|}{\frac{\left(|y_i| + |\hat{y}_i|\right)}{2}} \tag{3}$$

$$\text{Absolute percentage Error } (MAPE) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{y_i}\right| \tag{4}$$

2.4. Predictive Models

2.4.1. Multi-Layer Perceptron

Multi-Layer Perceptron (MLP) is a neural network architecture consisting of an input layer, an output layer, and a single or more hidden layers for many stacked neurons. In the perceptron model (Hrizi et al., 2022). A neuron is required to include an activation process. A function imposes a threshold, such as the sigmoid function (Abu Al-Haija et al., 2022). However, in the case of multi-layered sensory perception, Neurons have the flexibility to use any arbitrary activation function (Miller et al., 2018). The diagram provided shows the structure in **Figure 1**. The components of the multi-layer Perceptron network.

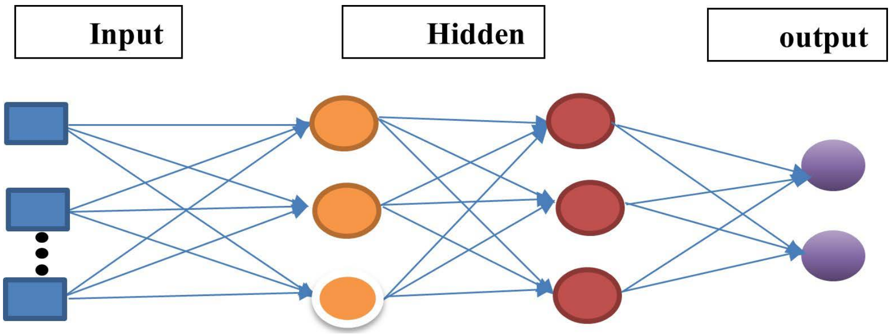

Figure 1. Multilayer perceptron network.

2.4.2. Decision Tree

Decision tree is a classification and regression modeling tool and is an example of an algorithm that uses supervised learning (Hamdi et al., 2023). Since regression is a technique for implementing predictive modeling, these trees can either classify data or make predictions about what will happen in the future (Kamiński et al., 2018). Decision trees are diagrams that resemble flowcharts, and start at the root node with a particular data inquiry. In the field of machine learning, decision tree algorithms are utilized for both prediction and classification purposes. With the use of the decision tree and a predetermined collection of inputs, one is able to map the numerous outcomes that are the result of the decisions or consequences (Povhan, 2020). The structure of DT follows a hierarchical tree pattern, wherein the central root node is surrounded on all sides by branches, internal nodes, and leaf nodes. Root nodes are the initial nodes situated at the inception of a decision tree. At this juncture within the tree, the population will commence to undergo segmentation into multiple groups based on the shared features they possess. The nodes that persist in the tree structure subsequent to the severance of the root nodes are commonly denoted as internal nodes. The term "Decision Node" is employed to designate these nodes. the leaf that Possesses Nodal Structures The plant's leaf nodes or terminal nodes are defined as the nodes located on the leaves that lack the ability to undergo further division into additional divisions (Povkhan, 2020). show the Decision Tree Classification Algorithm and presented in **Figure 2**.

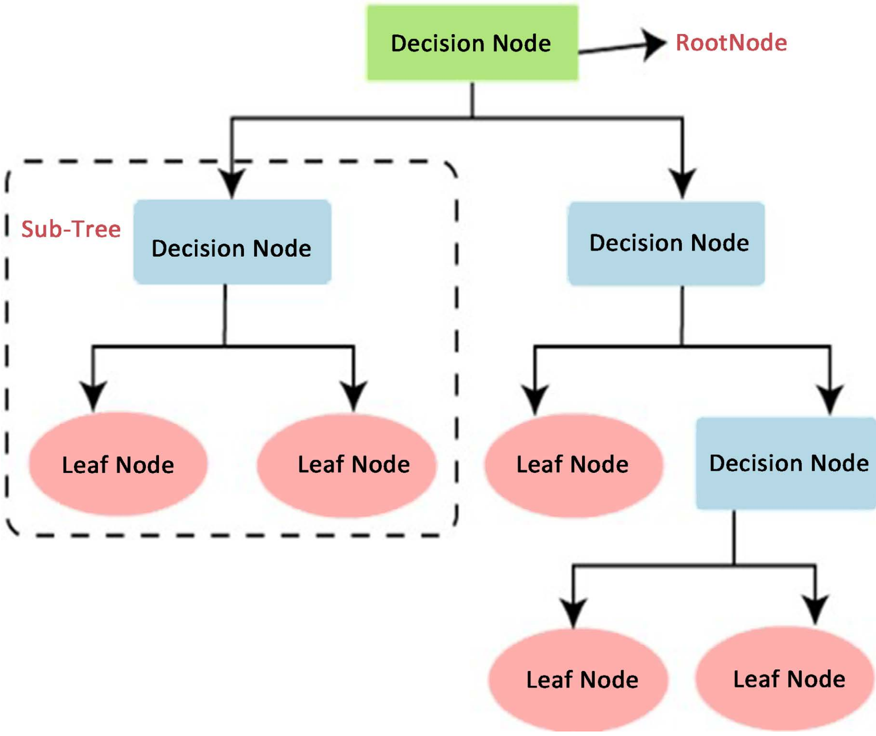

Figure 2. Decision tree classification algorithm.

3. Basic Definitions: Concepts and Hypotheses

3.1. Compliance Audit (CA)

Sarbanes-Oxley Act and other laws impose strict compliance standards, and businesses are forced to invest a lot of money to comply with them (Ghose & Koliadis, 2007). Timely implementation of Compliance shields businesses from fines and other legal repercussions from the government by assisting in the prevention and detection of legal infractions of laws or regulations (2022). Rules governing corporate governance are yet another important component of compliance. Violations of corporate governance regulations will raise operational risks within the firm, thereby impacting stakeholders' interests (Zerban & Madani, 2018). There is an increasing need to appoint a compliance officer and conduct compliance audits (Thottoli, 2022). The quantity, intricacy, and significance of the requirements for compliance are continuously increasing, prompting corporations to do so. Where various efforts are made to ensure compliance with legal regulations, regulatory standards or voluntarily imposed obligations (Panitz et al., 2010).

3.2. Balanced Scorecard (BSC)

One of the most recent developments in management is the Balanced Scorecard (BSC). Actually, it is a strategic instrument created by Kaplan and Norton and detailed in their book The Balanced Scorecard, published in 1996. Within the realm of business, the balanced scorecard has aroused intense curiosity at the international level (Nørreklit, 2003). The goal of the balanced scorecard is to find a solution of the background of finance metrics for accounting systems. This is done Through the incorporation of financial and non-financial strategic measurement variables into a cause-and-effect connection that presupposes the following: growth and learning inside the organization metrics → internal company operations process metrics → customer perspective metrics → finance metrics. Assuming a cause-and-effect relationship between the proposed measurement domains is crucial because non-financial measurements domains Apply feed-forward control to the performance measuring system (De Haas & Kleingeld, 1999). Measurement is as fundamental for managers as it has been for scientists (Kaplan, 2009). One study also concluded that the balanced scorecard approach may require some substantial changes in culture within the organization. A company's top management must comprehend, support, and be committed to the balanced scorecard. Balanced scorecards are going to evolve. The company will discover new metrics to use., and new objectives in several fields, to improve the effectiveness and balance of the balanced scorecard in achieving goals (Chavan, 2009).

3.3. Machine Learning Techniques (ML)

In order to increase performance in the future, machine learning is a model that may allude to learning from past experiences, which in this case are historical data. This field focuses only on autonomous learning techniques. Learning is the process of automatically adjusting or enhancing an algorithm without the need for outside assistance from a human based on prior "experiences" (Das & Behera, 2017). It is a subfield of artificial intelligence (AI), mainly concerned with computer algorithms that can automatically discover and learn from data. When ML is properly integrated with data analytics, it can ultimately maximize the use of big data AI and current computer technology. Innovations have led to the rapid creation of powerful deep learning (DL) algorithms that enable them to improve prediction and reduce involvement from humans (Surya, 2016). (ML) replaces its conventional statistical counterpart in forecasting future occurrences, which yields incredibly helpful findings and is applied in a variety of domains including engineering, the medical sciences, and finance (Sarkar et al., 2019).

Machine learning is of great interest in finding optimal solutions in various fields (El Misilmani & Naous, 2019). Machine learning is typically defined as a discipline that "concerns the question of how to create computer programs that get better on their own with use (Kuznetsov, 2004). Many methods based on statistics (Bayesian networks, instance-based approaches) and artificial intelligence (logic-based, perceptual-based techniques) have been developed (Kotsiantis et al., 2006). As evidenced by a number of current studies, machine learning approaches have garnered significant attention from the research community due to their superior classification accuracy when compared to alternative data categorization methods. Reaching extraordinary forecasting accuracy is essential because it can result in the right kind of protection (Dwivedi, 2018).

4. Results and Discussion

4.1. Multilayer Perceptron (MLP)

The data employed in this investigation, according to the MLP, included a total of 180 records (Table 1), of which 129 (71.70%) were used as training sets and 51 (28.30%) as test sets.

Table 1. Case processing summary.

		N	Percent
Sample	Training	129	71.70%
	Testing	51	28.30%
Valid		180	100.00%
Excluded		1	
Total		181	

Table 2 shows the units in the hidden layers: Sigmoid function is used for the dependent variable of the output layer (focus), and sum of squares is used as the error function. The activation function of the hidden layer is hyperbolic tangent.

Table 2. Model summary.

Training	Cross Entropy Error	71.613
	Percent Incorrect Predictions	23.3%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	0:00:00.02
Testing	Cross Entropy Error	26.978
	Percent Incorrect Predictions	25.5%
Dependent Variable: Compliance Audit		
a. Error computations are based on the testing sample.		

Figure 3 shows the Predictor pseudo probability" is a predictive model's projected likelihood or score of an outcome based on input predictors. It helps grasp and interpret model predictions in predictive modeling and machine learning applications, where strongly agree varied between 0.4 and 1.

Figure 4 shows the Impact of Input Changes on Neural Network Output Sensitivity suggesting a direct correlation between the input and output.

Figure 5 illustrates how the gain of the network affects its output, with a steeper line indicating a higher gain. High gain amplifies the input signal to a greater extent, which can have both advantageous and possibly destabilising effects.

4.2. Decision Tree (DT)

Classification and Regression Tree (CRT) is used as a growth methodology. The maximum depth of the tree is 3, the minimum number of cases in the parent node is 100, the minimum number of cases in the child node is 50, and the independent variables include 3 nodes. The number of end nodes is 2 while the depth result is 1. And shown in Table 3.

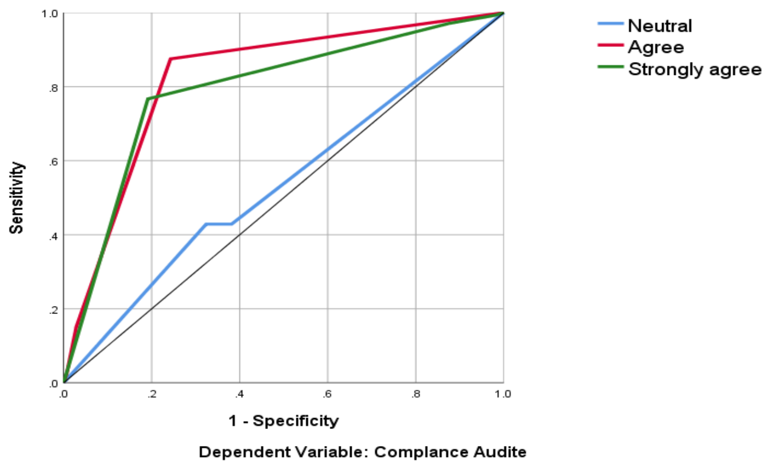

Figure 3. Predictor pseudo probability.

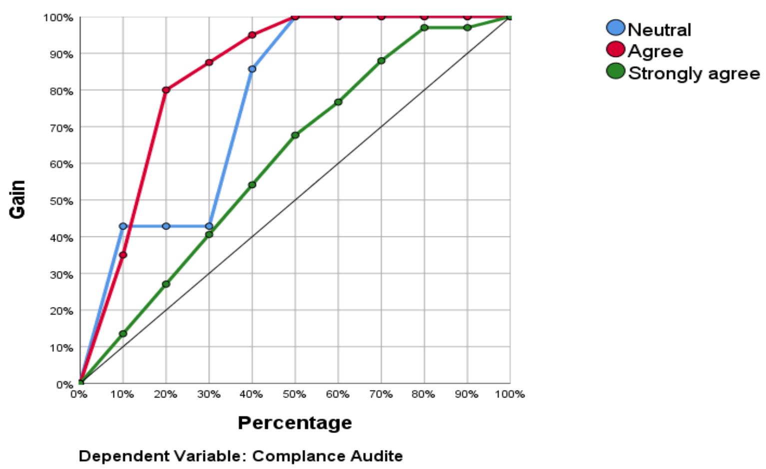

Figure4. The impact of input changes on neural network.

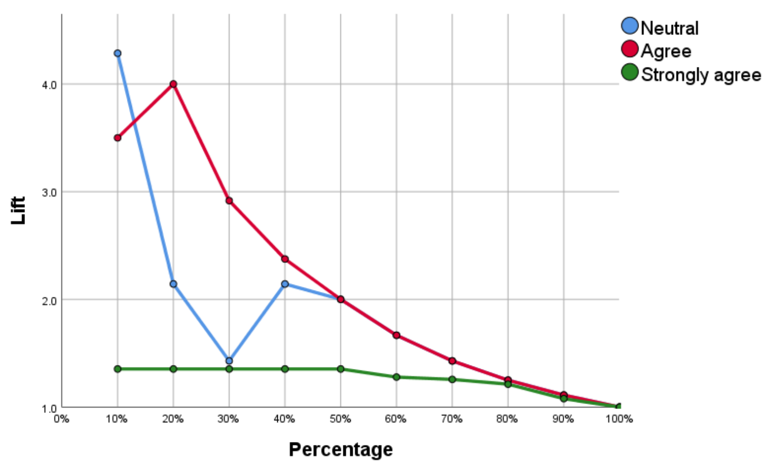

Figure 5. The effect of network gain on its output.

Table 3. Model summary.

Specifications	Growing Method	CHAID
	Dependent Variable	Compliance Audit
	Independent Variables	Balance Score Card
	Validation	Cross Validation
	Maximum Tree Depth	3
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	50
Results	Independent Variables Included	Balance Score Card
	Number of Nodes	3
	Number of Terminal Nodes	2
	Depth	1

It is clear from Table 4 that the degree of response of respondents in the study sample regarding the statements of the dependent variable reached 3 for strongly agreeing at a rate of 50% and 2 for agreeing at a rate of 33%, while the number of neutral ones was 1 at a rate of approximately 17%.

Table 4. Dependent variable scores.

Compliance Audit	Score
Neutral	1.000
Agree	2.000
Strongly agree	3.000

Figure 6 shows that the number of neutrals in node 1 is 3, those who agree are 35, and those who strongly agree are 31, and the total percentage for the first node is 38.3%. As for node 2, the number of neutrals is 4, those who agree are 4, and those who strongly agree are 102, and the total percentage for the second node is 61.7%.

4.3. Compare Prediction Values

One of the most straightforward ways to interpret forecast values is to compare them across different forecasting models or techniques. In general, lower prediction values indicate higher accuracy, while higher prediction values indicate less accurate predictions. Looking at Table 5, it was found that the prediction accuracy measures in the decision tree model are low compared to the multi-layer receiver model, which indicates the prediction accuracy of the decision tree model.

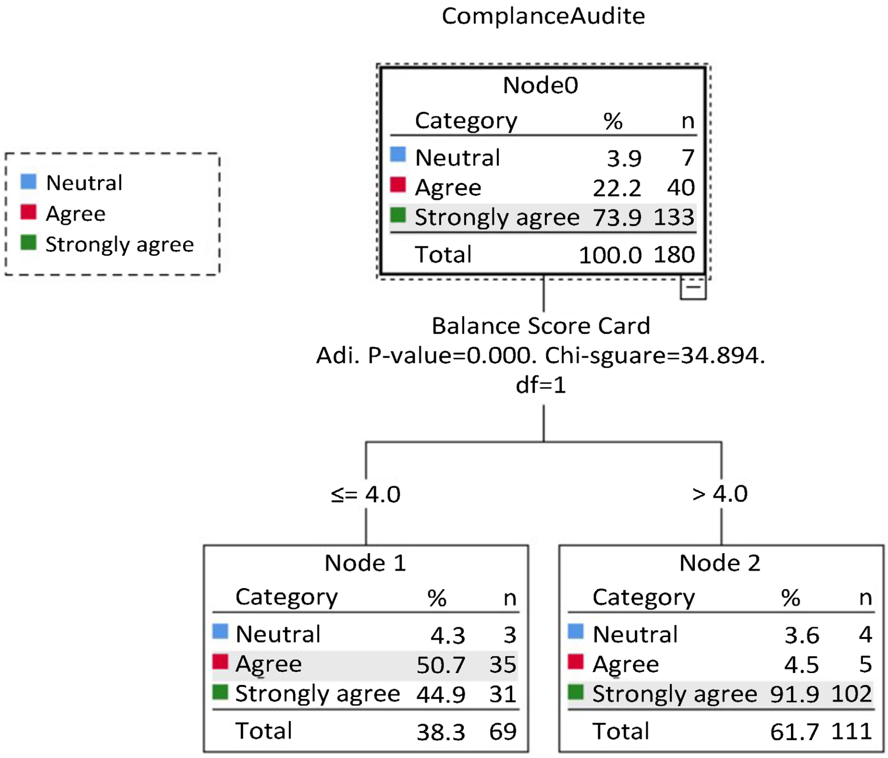

Figure 6. Structure of a training sample a decision tree with two nodes.

Table 5. The statistical metrics.

	DT	MLP
Mean square error	0.303867	0.861111
Root Mean square error	0.551242	0.927961
symmetric mean square	0.059984	0.206526
Mean absolute percentage error	6.141805	22.05341

5. Conclusion

Prediction models have many applications in the field of auditing. Both statistical and machine learning methods have been used for this task in many studies. This study combines two tools, the balanced scorecard and predictive analytics, to provide better prediction of compliance audit results, which has been achieved by Sudanese insurance companies by Through a machine learning perspective.

Among the study's findings is that including balanced scorecard data enhances the predictive capabilities of machine learning models, enabling organizations to identify compliance risks that are compatible with their strategic objectives. The implications of this research are also important as it offers organizations a proactive approach to compliance management as well as the ability to anticipate compliance issues through machine learning-based predictions. This, in addition to the insights from the Balanced Scorecard, enables decision makers to allocate resources strategically and align compliance efforts with broader organizational goals.

This study provides valuable insights into the synergy between compliance audit prediction, machine learning, and the balanced scorecard, providing a promising avenue for organizations to enhance their compliance management strategies and overall performance.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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