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Audit Risks and Prevention Strategies of Corporate Accounting Based on Computer Technology

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Abstract: - Business owners use professional auditors to do audits on their companies because auditors are essential partners in the growth of enterprises. Auditors may improve their ability to organize their audit work sensibly and provide accurate audit opinions if they effectively identify the risks associated with the audit. In this day and age of big data and the World Wide Web, businesses produce a significant quantity of data through the normal course of their activities. Using data mining techniques, deep learning, neural networks, and other developing technologies to extract excellent auditing data from the massive amounts of data produced by audited businesses is a significant challenge for auditors. As a result, the purpose of this research is to use computer data mining methods in order to develop an audit risk model. This model will give an example for auditors to use when doing big data analysis and will mine important data, which will ultimately result in an improvement in the audit process's efficiency as well as its correctness.

Keywords: Audit risks, Data integrity risks, System security risks, Computer technology, System reliability risks , Fraud risks.

1. Introduction

As a result of businesses undergoing a digital transition, both the manufacturing and the management operations of businesses are now being handled almost entirely by information technology.
(Hafadh and Flayyih) In this, auditors must contend with an audit environment that is both more complicated and diversified in order to carry out their task. In today's risk-based auditing, auditors are required to concentrate the little audit resources they have on areas of greatest risk, which creates additional demands on both inspectors and audit work. In addition, the steady flow of audit-related errors in the stock market over the last several years should serve as a reminder to auditors that they need to improve their ability to identify audit risks. Audit models take on the role of combining corporate data with audit results as part of the method of digital audit analysis.. (Han et al.)
In order for an auditor to deliver an accurate audit opinion and produce an audit report, it is essential that the audit be carried out in an appropriate and effective manner. It is possible to use the audit report, which is an assurance report that was provided by an independent auditor, to determine whether or not the activities, financial situation, and revenue streams of the business being audited are in compliance with the legal requirements. Furthermore, the audit report may play an essential function as a source of information for shareholders as a guide for investments, shareholders of the business to assess the achievement of the management, and appropriate authorities for market oversight. All of these parties can benefit from having access to the audit report.
(Putri et al.)Therefore, if auditing hazards are not successfully detected, it will have a negative impact on the standard of audit work and prohibit auditors from giving right audit views.
According to, (Smith et al.)Utilizing information technology may assist in steering auditing work in a more quality-focused direction. However, one of the most significant challenges that auditors have is determining how to make efficient use of information technology within the vast quantities of accounting data in order to accomplish accurate identification of audit risk. The ever-increasing quantity of digital information necessitated the development of a novel technique for the processing of information, which is known as data mining. It is able to identify new, hidden, or unexpected patterns or actions in data in an automatic manner, often removing the element of human discovery from the process.
According to,(Yeshmuratova et al.) These patterns or actions are discrete pieces of data that are buried deep inside massive data warehouses, databases, or other enormous information repositories. Data mining is a process that leverages the information that is stored in data warehouses in order to find problems that audits may not have been paying attention to in the past. This is due to the fact that the area of data mining is home to a wide variety of algorithms. In actual fact, most algorithms for mining are not utilized on their own but rather are integrated with a

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variety of additional techniques in order to get the required outcomes. Therefore, it is essential to make use of data mining methods in order to enhance the auditors' capability of identifying audit risks. , (Smith et al.)

1.1Literature Review

According to, (Putra and Fianty) the auditor may have delivered an inappropriate audit opinion. Errors resulting from audit risk may be broken down into two categories at a more granular level. There are mistakes in the data of the different categories of accounting information that are conveyed by the financial statements that are brought about by the audited business itself for a variety of reasons (Shaikh and Siponen)

On the other hand, there are mistakes in the data that are produced by external factors. On the other side, there are instances in which the auditor failed to identify flaws in the accounting information, which might lead to improper audit judgments (Afriyie et al.)[8]. Audit risk, as pointed out by Sinaga and Emirzon, comprises not only the usual risk of an auditor giving an improper audit opinion. (Kedah)[9]. This is because audit risk contains both the traditional risk and the risk of misstatements.

According to, (Yeshmuratova) audit risk is the chance that the independent auditor has failed to discover or completely identify the accounting fraud of the audited business as a consequence of the procedure for auditing. They then made a recommendation to improve the data-based audit standard system (Alkaraan et al.)

There are a number of elements that contribute to audit risk, each of which has been investigated by academic scholars approaching the topic from a unique angle. In general, they may be broken down into two distinct categories: the firm's internal elements and the external environment in which it operates. The legal system(Mökander et al.) , market competitiveness , and audits by third parties are the primary elements that determine audit risk in the external environment.

(Hafadh and Flayyih) Additionally, various legal systems might have an effect on audit risk; hence, it is essential to make sure that responsibility and authority are well-defined.. Price volatility was shown to have a strong correlation with audit risk. This was due to the fact that businesses operate in an environment that is extremely competitive. Accounting firms, in their capacity as professional third-party auditors, have the ability to impact the evaluation of audit risk for corporations. This effect might be a result of the relevant industry audit expertise of the firm, the nature of the company itself, or the firm's controls and systems (Bai and Yao)

Scholars have concentrated on audit fees, controls within the company. In addition, there are numerous variables inside a firm that might have an influence on audit risk. He did this so that he could study the relationship between the two observed that characteristics.

According to,(Gu et al. 4) The researchers quantified audit risk via audit fees. They came to the conclusion that audit risk may be lowered by means of enhancing the level of oversight. This finding pertains to both internal auditing and corporate governance.

According to, (Afsay et al.) In addition, this can help companies accomplish the purpose of curbing audit risk. In addition, the variables impacting risk associated with audits from other parts of the organization have been researched by a number of scholars who have done further study. Musallam discovered that corporate leadership is often placed under significant pressure as a result of changes in the firm itself. This presents an important reason for them to participate in fraudulent activity, and it frequently results in a danger of serious falsification in the accounting records.

According to, (Murugan and T) found a substantial positive association between power in leadership and audit risk. She came to the conclusion that the more authority managers have, the greater the likelihood that they would pursue personal benefit, which in turn leads to a rise in audit risk

One of the most important questions that has arisen with the expansion of auditing is how to recognize and evaluate audit risk. For risk recognition and assessment in today's world, researchers mostly rely on audit risk models, classifications, and analyses of the components that have an influence, and they combine these methods with real-world situations.

According to,(Bandari) They did this by including components such as substantial deformation risk and unnoticed risk in their model. They also proposed an update of the ARM that breaks down the traditional framework down to the level about simple distinct statements.

According to,(Savić and Pavlović). In order to develop the audit detect risk assessment system, used a hybrid approach that included both traditional fuzzy theory and the audit risk model. When compared to the conventional method of assessing the risk of discovery, this methodology has the potential to dramatically improve audit quality.

According to, (Wu) conducted research on ARM in enterprise resource arrangement environments and discovered that there are no discernible variations in the ways in which Canadian and Chinese auditors analyze comparable data in order to construct their risk assessments.

2. Methodology

Data mining is the process of using various algorithms to look for information that may be buried inside a big quantity of data. In order to create an audit strategy that is based on information analysis and mining, the primary emphasis of this study is on the application of methods made available by algorithms developed by computers to the examination of enormous amounts of data.

2.1. Neural Network of the BP

A kind type artificial brain network known as the neural network made up of BP is described here. This is accomplished by emulating the structure and functioning of the nervous system of the brain, which is accomplished via the process of forward transmission of learned signals and reverse propagation of errors in the network.

The topology of a traditional neural network is shown in Figure 1. This structure includes a layer for input, a hidden layer, and a layer for output.

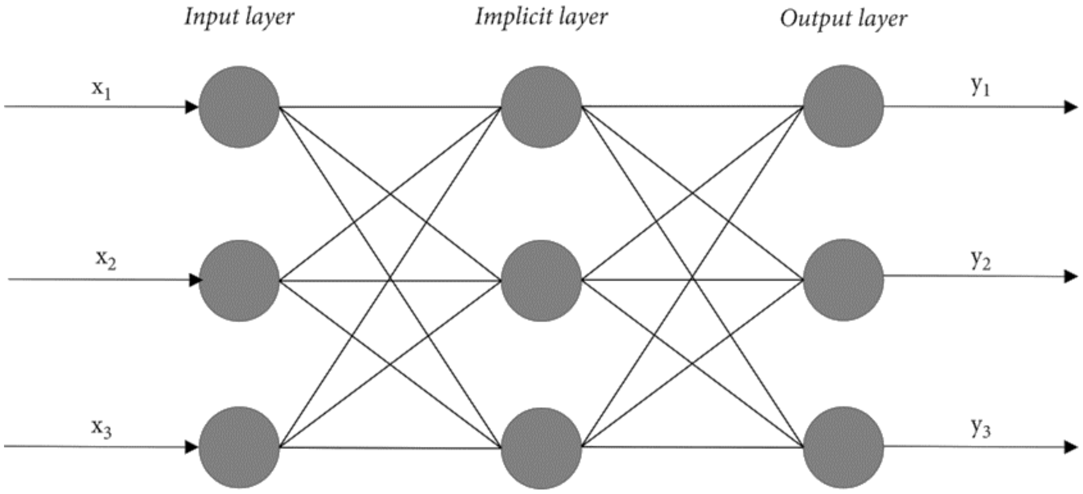

Fig.1. The algorithmic structure of a BP neural network Adopted from (Niu et al.)

The initial information to be learned is taken in by the input layer, then passed on to the implicit layer for processing, and is eventually outputted by the layer designated as the output layer.As a result, the final output value is able to match the error requirement, which enables model optimization learning to take place.

$$f(\sum_{I=1}^{N} Wi\, X\, x_i - b_i) \quad (1)$$

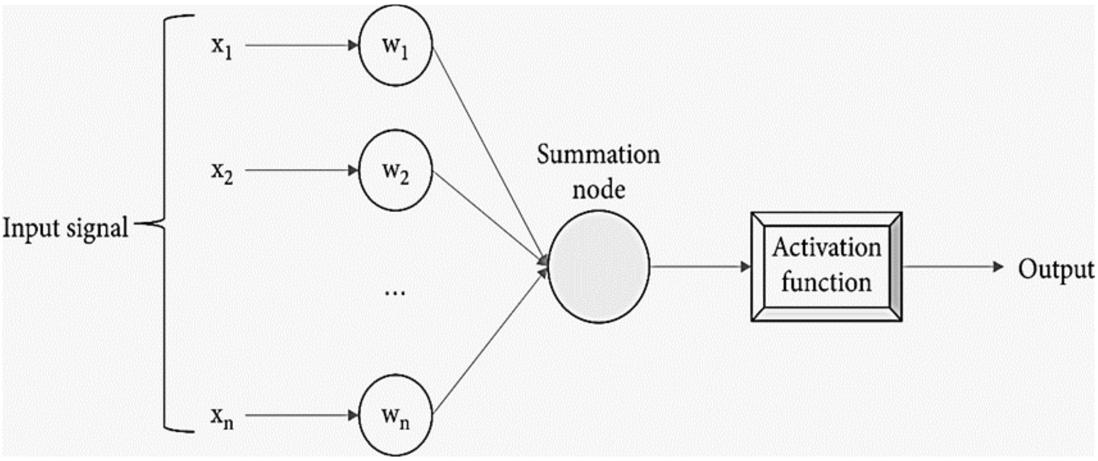

Fig.2. depicts the construction of a BP neural network. Adopted from hindwai. (Niu et al.)

The input of several pieces of information, which are subsequently operated on by the training function after the biological neuron has been abstracted and simulated, results in the production of just one bit of information as the output. The activation function, also known as the mapping function, is another name for the intermediate run function, and its notation looks like this.

$$\boldsymbol{Vi_j = nX \sum_{k=1}^{i} \delta k\, XW_{ik} X z_i X(1 - z_i) X x_i} \quad (2)$$

The conventional neural network BP algorithm is the gradient descent method.
In addition to having superior handling of linear or nonlinearly correlated data, one of the most important characteristics of BP neural networks. The BP neural network method may be customized to operate with a variety of different sample data types for the purpose of audit risk detection. In addition, the precision of the model may be improved by acquiring new knowledge and honing existing skills. In addition, the neural network algorithm developed by BP may be used for a variety of auditing procedures. In order to handle limited quadratic planning issues.. The idea of support vector machines (SVM) is frequently used in pattern recognition and nonlinear regression. This concept may be summed up as "maximizing the area on both sides of the hyper plane." To put it another way, the goal of a machine known as a support vector machine is to minimize the amount of structural risk that is incurred.
The traditional linear transformation means are ineffective when the training sample data cannot be differentiated from one another. In order to create a nonlinear support vector machine, SVM employs a nonlinear transformation. This transformation is implemented by selecting a kernel function, optimizing the soft interval, and using a hyper surface model and space of features that are compatible with the input space.

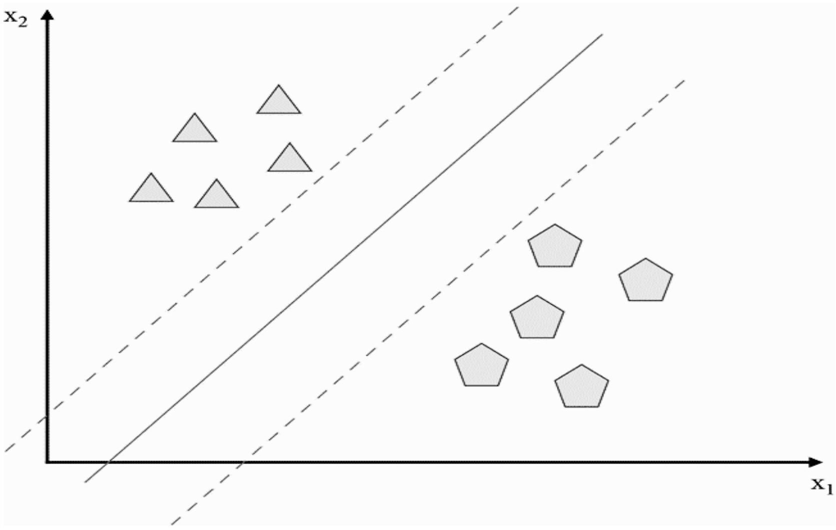

Fig.3. illustrates the specifics for your perusal. Adopted from hindwai(Niu et al.)

In the end, it is possible to acquire an optimum classification hyper plane that is focused on reducing structural risk. This allows for the samples as a whole to be categorized in the most effective manner.
The optimal classification function can be expressed as follows:

$$f(x) = sgn\left\{\sum_{i=1}^{l} a_i X y_i X x_i + b\right\} \quad (3)$$

2.2. Audit Model Formulated on the Basis of Data Mining Algorithms

The Method of the Building Inspection Process:
(1) The gathering of data. When a sample topic has been chosen, the next step is to gather data on that subject from the appropriate online portals, platforms, and databases. This is done mostly by keyword searches, web crawlers, and other similar methods.
(2) The selection of data features. The most important stage is to choose feature variables that are appropriate for classification in order to reduce duplication and complexity and enhance the performance of the classifier.
(3) The preliminary processing of sample data. The use of specialized technological tools that normalize data that does not fulfill experimental standards is what is meant by the term "sample data preprocessing." Common ways include data cleansing, integrating data, data transformation, and data simplicity. Because the outcomes of following tests are directly influenced by the findings of this stage, it is of the utmost importance.
(4) Thorough examination of both the errors in the calculations and the findings of the experiments. In order to acquire the best possible results from the classification recognition model, its test results are compared and analyzed with the predicted value. Based on this information, the algorithm parameters are then updated at the appropriate times in order to bring about a continual improvement in the model's performance.

3. Results and Discussions

The method known as random forest is used for classification and recognition. It does this by using multimodal decision trees. Because their visual representations are so like to the trunks and limbs of actual trees, decision trees have been given that moniker. The decision tree extends various nonleaf nodes depending on the chance of getting a characteristic value, using an attribute's value as a threshold. As a result, it is able to integrate all attribute features and, as a consequence, define the particular classification criteria associated with each classification result. In the domains of making decisions about projects and doing risk assessments, decision tree structures are one of the primary methodologies that are employed. When the decision tree is put to use for prediction classification, the mapping of characteristics to values that occurs among the base node and each of the other nodes in the tree is known as the mapping.

Now, Figure 4 illustrates the flowchart representation of the decision tree. The root node serves as the starting point for decision trees. In the process of actually classifying things, if an attribute test is successful, the tree moves on to the nonleaf node A for the next branch step, and if it is unsuccessful, the tree moves on to the nonleaf node B. The outcome of the categorization test is shown by the data that is produced by each node.

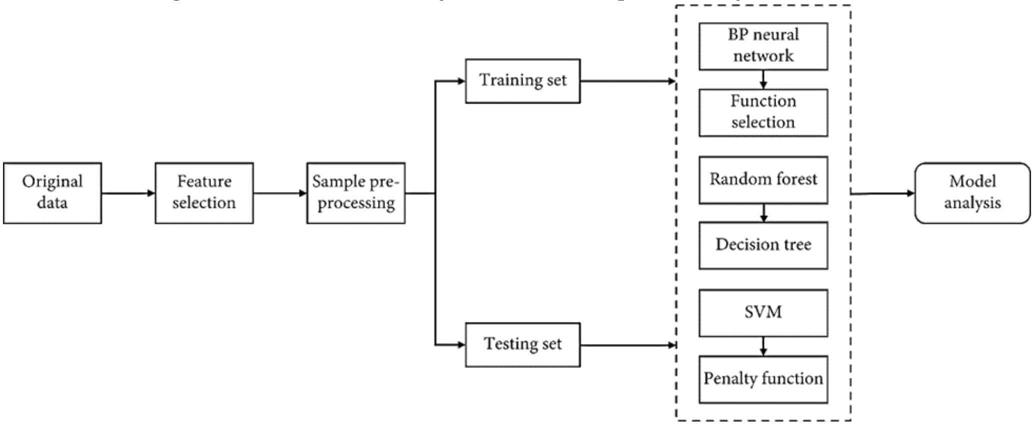

Fig.4. Audit risk model workflow using data mining techniques

The random forest algorithm then makes use of the decision tree that has been trained to choose the ultimate categorization result. In the first step, the Bootstrap technique is used to repeatedly sample the training set. The results of these repetitions are then used to generate training sets. After that, these training sets are included into the process of training and generating decision trees. In order to generate the nonleaf nodes of the tree of choices, rather than selecting the complete amount of characteristics, a random selection of attributes is made from them, and the tree is then branched in the way that produces the optimal split. In the end, the category on the decision tree that garners the most agreement is the one that is utilized for the final categorization of the test set, and majority voting is employed to determine this.

Figure 5 depicts the steps of the procedure in detail.

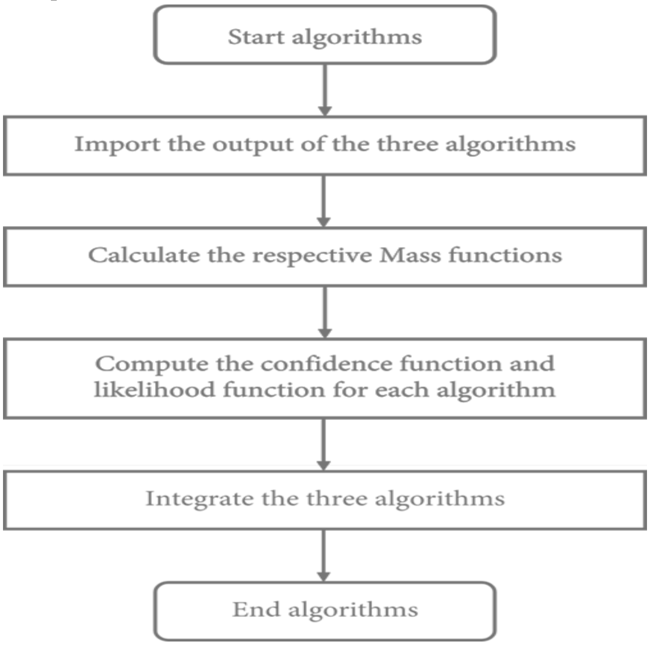

Fig.5. Algorithms for data mining are being combined

4. Conclusion

As of right now, the marketplace is changing fast, and auditors are confronted with an audit environment that is more diversified and complicated.It is now possible to employ data mining methods for auditing, thanks to the maturation and enhancement of big data architecture and design. The necessary hardware and software are now readily accessible. Within this framework, the research in question develops an audit model by utilizing data mining methods. However, in order to get beyond the limitations of those algorithms, this research also combines all three of them. The model improves the decision support provided by the identification models by implementing secondary processing on the output of three different models that identify audit risks. Additionally, the model provides value for both practical and theoretical applications.Due to the fact that these models are essentially black boxes, they have a low level of interpretability, which precludes them from elucidating the function of each feature.. This will allow for more accurate predictions to be made. In order to enhance the model, the parameters of the model should first be improved, and then various machine learning methods should be used. It is recommended that further machine learning techniques be used in order to enhance and perfect the audit risk detection model. Following research could further categorize audit risk levels on an individual basis in order to address the deficiency of a refined categorization of audit risk levels.

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