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Presenting the Development of the Beneish Model with Emphasis on Economic Features using Neural Network, Vector Machine, and Random Forest

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Abstract

As the business process becomes more complex, financial statement distortion risk increases. In this regard, researchers have been looking for models to detect fraud in financial statements. Beneish (1997) predicted earning manipulation using financial ratios and accruals. Since economic pressure is presented as a manager's external motivation to manipulate income, the Beneish model is developed based on economic variables, including Inflation Rate, GDP Growth, Exchange Rate, and Economic Growth Rate. The fitting of the random forest, vector machine, and neural network was used to fit the extended model. The results show that the accuracy of the random forest model is 99.96% which is more than the neural network and vector models, 96.1% and 93.62%, respectively. The final results show that the developed model is more accurate than the basic Beneish model. The results show that economic factors play a significant role in fraudulent financial reporting which should be considered when analyzing financial reporting.

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1. Introduction

Today, fraud is considered the most severe threat to the public interest and the capital market, which has quadrupled over the past decade and its destructive effects continue. The global cost of fraud is estimated at over $ 3.5 trillion annually. This allows for a specialized look at the factors that lead to fraud and ways to prevent it. According to the concept of the fraud triangle, pressure, opportunity, and justification are the factors that cause fraud. One of the pressure factors on companies' fraudulent reporting is economic pressure (Ahmad et al., 2021). Classification of types of financial reporting can be done as follows: 1) conservative 2) neutral 3) aggressive, and 4) fraudulent (Dechow and Skinner, 2000). If the economic situation of countries is not good, pressures on the company's management will affect earning manipulation and fraud. National Commission on Fraudulent Financial Reporting (NCFFR) in 1987 defined fraudulent reporting as the intentional use of a procedure or the non-application of a process that resulted in a material misstatement of the financial statements. Jofre and Gerlach (2018) believe that accounting fraud aims to mislead shareholders about the correct financial situation by overstating expectations of assets or underestimating debts, leading to an artificial overstatement of earnings or equity returns.

2. The Conceptual framework and literature

Association of Certified Fraud Examiners (ACFE) provided a comprehensive overview of the general practice of financial statement fraud, according to which although financial fraud is more unusual than corruption and misuse of assets, the cost of each event averages $ 800,000 compared to the average of $ 250,000 corruption and average $ 114,000 asset misuse. Therefore, many researchers have sought to predict fraud using financial statement variables. Beneish (1997) used financial ratios and accruals to predict profit manipulation methods. He used three sources to select explanatory variables due to the lack of appropriate economic theory to manipulate financial information. The first source is to examine the future signs of the company. He explained that profit is more likely to be manipulated when the company's weak future position is weak. The second source, based on the model of Jones (1985), was the selection of variables based on cash flows and accruals. Finally, based on the positive theory of Watts and Zimmerman (1986), he used the contractual hypothesis. The result of his study was the development of an eight-variable model based on financial statement data. In his modeling between 1997 and 1999, Beneish stated that companies that manipulate their financial information do not use only accruals, and different variables should be used to determine financial information manipulation. These variables help identify companies that manage profits or companies that do not perform their transactions according to accepted accounting principles (Beneish, 1997, 1999).

To develop the Beneish model, four economic variables as following is added to the model:

2.1. Inflation

Inflation has long been considered one of the most important economic variables affecting fraud. The relationship between inflation and fraud is one of the most controversial issues among researchers. Under inflation conditions, companies' nominal profits increase over time. However, the profitability of companies has not increased. Another effect of inflation is that it reduces the intrinsic value of each share. In years when inflation is high, the quality of companies' real earnings (economic income) decreases (Ahmad et al., 2021).

2.2. Gross domestic product

Gross domestic product is the market value of all the final goods and services produced in a country over a year. Gross domestic product in each year represents the total performance of economic sectors in the use of resources and production of goods and services. Gross domestic product and its components include many figures related to the performance of enterprises. Corporate income is an essential component of GDP, from which investors pay dividends. Therefore, it is reasonable to say that investors will push stock prices to increase if they anticipate a boom in economic conditions (Pezhoyan and Azizi, 1999).

2.3. Exchange rate

The exchange rate, as a measure of the value of a country's national currency against the currencies of other countries, reflects that country's economic situation compared to other countries' economic conditions. The real exchange rate is a critical variable in an open economy because of its interrelationship with other economic variables, which are greatly influenced by domestic and foreign economic policies and developments. One of the critical issues in real exchange rates, especially in underdeveloped and developing countries, is the instability and the intensity of exchange rate fluctuations and their effect on the performance of various macroeconomic variables and sectors (Avdjiev et al., 2018).

2.4. Economic growth

In simplest terms, economic growth refers to an increase in aggregate production in an economy. Often, but not necessarily, aggregate gains in production correlate with increased average marginal productivity. That leads to increased incomes, inspiring consumers to open their wallets and buy more, which means a higher material quality of life or standard of living. Shakouri et al. (2021), using data from 161 companies on Tehran Stock Exchange from 2009 to 2018, showed that the Beneish model could separate fraudulent companies from non-fraudulent companies. They showed that the accounts receivable index, profit margin index, asset quality index, sales growth index, depreciation index, and total assets accrual index have a positive and significant effect on fraudulent reporting. In contrast, the public, administrative, sales expenses and leverage index significantly negatively affect fraudulent reporting.

Rahimian and Haji Heidari (2019) show that the ratio of sales to total assets and equity to total assets are two financial ratios sensitive to fraud. Their model has an overall accuracy rate of 69.1 percent. Shirazi Dehqavarkhani and Haghgoo (2018) conducted a study entitled "Investigating the relationship between business strategy and fraudulent financial reporting," emphasising the role of disclosure quality in companies listed on the Tehran Stock Exchange. Their results show that a defensive management strategy has a negative effect on fraudulent financial reporting, but an aggressive management strategy positively affects fraudulent financial reporting. The disclosure quality negatively affects the relationship between defensive management strategy and fraudulent financial reporting. But this variable does not significantly affect the relationship between aggressive management strategy and fraudulent financial reporting. Ebrahimi et al. (2017) conducted a study entitled determining the effect of audit quality and shareholders' rights on fraudulent reporting in financial statements. Their results show that audit quality has a negative effect on fraudulent reporting in financial statements. The results of their research also show a negative relationship between compliance with shareholders' rights and the possibility of fraudulent reporting.

Jamali (2016) investigated the relationship between selective corporate governance mechanisms and audit quality on the occurrence of fraud in the financial statements of companies listed on the Tehran Stock Exchange. Testing his hypotheses showed that the independence of board members, ownership percentage, the quality of the audit firm, and the tenure of the board chairman have a negative effect on fraud. However, the CEO's dual role, losses in the previous two years, and the auditor's tenure positively affect the likelihood of fraud in the financial statements. Finally, the number of board meetings, the size of the audit firm, and the ownership of institutional shareholders do not affect the likelihood of fraud.

Erdoğan and Erdoğan (2020) used the Beneish model to examine fraudulent companies on the Istanbul Stock Exchange. After identifying fraudulent companies, they obtain a positive relationship between fraudulent financial information and the index of asset quality and public, administrative, and sales expenses.

Li and Zaiats (2018) focus on the corporate information environment, examining the extent of profit manipulation by companies operating in a poor information environment. They showed that companies with high information asymmetries, and inadequate information environment, have a good platform for profit manipulation, and managers of these companies are more motivated to manage profits. Companies that are good at disclosing information and reporting on time and for various reasons have created a transparent information environment for users of financial statements to be less likely to manage profits.

Research Hypotheses:

1- Beneish model can predict the companies manipulating earnings.

2- The developed model of Beneish has more predictive power than the original model of Beneish.

3. Research Methodology

This research is applied research, and the research method is descriptive-correlational research. In addition, in the present study, after selecting the effective variables, a model was developed and presented. The present study is quantitative and archival research according to the data type. In addition, SPSS software is used to test research hypotheses.

3.1. The statistical population of the study

The statistical population of the research is the companies listed on the Tehran Stock Exchange. Due to the available audited information of companies operating in the stock exchange, this population has been used to study research models. The research sampling method is a systematic removal method that is used to homogenize the selected sample and increase the comparability of the sample, which includes the following limitations:

1. The information required for the research should be available; 2. Since the research period is from 2011 to 2019, sample companies should have been listed on the stock exchange before the fiscal year 2011. 3. Sample companies are not listed in banks, financial institutions, investment funds, or

leasing industries. To increase the comparability of their fiscal year information, it should end in the Esfand month. According to the sampling conditions, 139 companies were selected as a statistical sample.

3.2. Data analysis

In this research, the main model of Beneish is first tested and compared with its developed model.

The primary model of Beneish:

$$EM = a_0 + a_1 DSRI + a_2 GMI + a_3 AQI + a_4 SGI + a_5 DEPI + a_6 SGAI + a_7 ATA + a_8 LVGI$$

The developed model and research variables

$$EM = a_0 + a_1 DSRI + a_2 GMI + a_3 AQI + a_4 SGI + a_5 DEPI + a_6 SGAI + a_7 ATA + a_8 LVGI + a_9\, INF + a_{10}\, GDP + a_{11}\, EX + a_{12}\, GROW$$

The constituent variables of the Beneish model:

Days Sales in Receivables Index (DSRI): Due to changes in credit policies to increase sales, an increase in the receivables ratio (REC) to sales (SALES) occurs, but an abnormal rise in receivables also leads to an increase in revenue (Beneish, 1999).

$$DSRI = \frac{REC_t / SALES_t}{REC_{t-1} / SALES_{t-1}}$$

Gross Margin Index (GMI): If the gross profit margin exceeds 1, the gross profit margin has decreased significantly. The weakening of gross profit margin gives a negative signal to the company's outlook and increases the likelihood of earning manipulation (Beneish, 1999). In this regard, SALES is the company's annual sale, and COG is the cost of goods sold.

$$GMI = \frac{SALES_{t-1} - COG_{t-1} / SALES_{t-1}}{SALES_t - COG_t / SALES_t}$$

Asset Quality Index (AQI): If the asset quality exceeds 1, the company pays deferred costs and intangible assets, increasing the likelihood of earning manipulation (Beneish, 1999). In this regard, CA is the current assets and PPE of property, plant, and equipment, and ASSETS is the sum of assets.

$$AQI = \frac{1 - (CA_t + PPE_t)/ASSETS_t}{1 - (CA_{t-1} + PPE_{t-1})/ASSETS_{t-1}}$$

Sales Growth Index (SGI): High sales growth does not imply manipulation. High growth companies are more likely to commit financial fraud because their financial position and capital pressure managers to achieve earnings targets. If growth firms face large stock price losses at the first indication of a slowdown, they may have greater incentives to manipulate earnings.

$$SGI = \frac{SALES_t}{SALES_{t-1}}$$

Depreciation (DEPI): A falling level of depreciation relative to net fixed assets raises the possibility that a firm has revised the estimated useful life of assets upwards or adopted a new method that is income increasing. DEP, in this formula, is depreciation.

$$DEP = \frac{DEP_{t-1}/PPE_{t-1}}{DEP_t/PPE_t}$$

Leverage Index (LVGI): Leverage is measured as total debt relative to total assets. An increase in leverage creates an incentive to manipulate profits to meet debt covenants. LTD is long-term debt, and CL is current liabilities.

$$LVGI = \frac{LTD +_t + CL_t/ASSETS_t}{LTD_{t-1} + CL_{t-1}/ASSETS_{t-1}}$$

Sales, General and Administrative Index (SGAI): Analysts might interpret a disproportionate increase in SG&A relative to sales as a negative signal about a firm's prospects, thereby creating an incentive to inflate profits. SGA EXP is Sales, General, and Administrative Expenses.

$$SGAI = \frac{SGA\ EXP_t/SALES_t}{SGA\ EXP_{t-1}/SALES_{t-1}}$$

Total Accruals to Total Assets (TATA): Total accruals are calculated as the change in working capital (other than cash) less depreciation relative to total assets. Accruals, or a portion thereof, reflect how managers make discretionary accounting choices to alter earnings. Higher accruals are associated with a higher likelihood of profit manipulation. ACC is accruals calculated as the difference between operating cash flow and operating income.

$$TATA = \frac{ACC_t}{ASSETS_t}$$

3.2.1. Variables added to the Beneish model

Inflation rate (INF): The percentage change in the price index over a period (usually one year).

GDP Growth (GDP): is the sum of the Rial value of all final goods and services offered in the country over a specified period (usually one year).

Exchange Rate (EX): Price of a foreign currency (Dollar) in the national currency.

Economic growth rate (GROW): The increase in a country's production in a particular year compared to its value in the base year.

4. Data analysis

The results of data analysis using SPSS24 software are shown as descriptive and analytical statistics. The central limit hypothesis in probability theory states that if we sample a large number of an arbitrary distribution (with a sufficiently large number equal to 30), the mean sample distribution will move to the normal distribution; normally test is ignored in this study. To investigate the significant relationship between the Pearson correlation coefficient, Vector Machine and Random Forest Model and Neural Network are applied to fit the models.

4.1. Descriptive Statistics

Descriptive statistics provide an overview of how research data is distributed. The results of descriptive statistics are shown in Table 1.

Table 1. The Descriptive statistic

Variable	Mean	Std. Dev.	Min	Max
TATA	0.020	0.140	-0.630	1.350
LVG	1.010	0.420	0.060	12.290
SGA	1.870	3.610	-2.210	43.440
DEP	2.270	14.040	0.010	465.760
SG	1.322	1.740	0.000	57.050
AQ	1.390	4.570	0.010	106.700
GM	1.650	6.900	-45.880	136.650
DSR	15.170	380.890	0.000	12771.020
INF	22.800	11.290	9.000	41.20٠
٠EX	58.440	65.660	12.260	217.920
GROW	0.370	6.010	-7.70	12.500
GDP	1.870	3.650	-6.610	4.470

As is shown in Table 1, the maximum inflation is 41.2, which is for the year 2019, and the minimum is 9, which is for the year 2017. GDP and GROW have negative and positive growth years in the sample period.

4.2. Beneish Model

The Beneish model is fitted with 3 methods: Vector Machine, Random Forest, and Neural Network.

4.2.1. Vector Machine Method

Vector Machine is one of the data mining methods used for forecasting. Its most important task is to prioritize the variables affecting the dependent variable that enter the model in order. The results are shown in Table 2

Table 2. The Model by Vector Machine Method

Variables	Coefficient	Priority
TATA	0.020	Sixth
LVG	1.019	Seventh
SGA	1.855	Eights
DEP	2.249	Fifth
SG	1.336	Fourth
AQ	1.405	Third
GM	1.666	Second
DSR	15.174	First

According to the fitted Vector Machine model, the regression coefficients estimated in the Table are as above and the estimated fraud model is as follows:

$$MScore1 = 0.02TATA + 1.019LVG + 1.855SGA + 2.249DEP + 1.336SG + 1.405AQ + 1.666GM + 15.174DSR$$

The accuracy of the model is presented as follows:

Table 3. The Accuracy of Vector Machine Method

Beneish model	Accuracy
0	16%
1	100%
Total	93.03 %

According to Table 3, the accuracy of the Vector Machine Method is 93.03 percent.

4.2.2. Neural Network Model

The resulting neural network architecture consists of 12 input layers (independent variables), 1 middle layer with 8 units, and 1 output layer (dependent variables). The performance function used in the middle layer is the hyperbolic tangent function and the error function applied is the mean squared. It should be noted that 69.7% of the data equivalent to 840 were used as a training sample, and 30.3% of the data equivalent to 366 were used as a testing sample.

Table 4. The Assign the number of sample members

		N	Percent
Sample	Training	840	69.7%
	Testing	366	30.3%
Valid		1206	100.0%
Excluded		45	
Total		1251	

According to table 5 the amount of error obtained from the fit of this model is equal to 161.834 in the training sample and the amount of error obtained in the testing sample is equal to 64.945. Since the amount of error obtained in the testing sample is less than in the training sample. Therefore, model fit is acceptable.

Table 5. The Comparison of model fit error

Training	161.834
testing	64.945

The effect of independent variables in entering the model is as shown in Table 6:

Table 6. The Neural network model variables

Variables	Coefficient	Priority
TATA	0.088	Fifth
LVG	0.211	First
SGA	0.076	Seventh
DEP	0.155	Third
SG	0.192	Second
AQ	0.060	Eighth
GM	0.086	Sixth
DSR	0.130	Fourth

Accuracy of the model presented in Table 7:

Table 7. The Accuracy of Neural Network

Training	Accuracy	Testing	Accuracy
21.04 %	0	26.4 %	0
99.7 %	1	99.6 %	1

According to table 7, the accuracy of a Neural Network is 99.7 percent.

4.2.3. Random Forest Model

Random forests or random decision forests are an ensemble learning method for classification, regression, and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct decision trees' habit of overfitting their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance. The first algorithm for random decision forests was created in 1995 by Tin Kam Ho using the random subspace method, which, in Ho's formulation, is a way to implement the "stochastic discrimination" approach to the classification proposed by Eugene Kleinberg.

Table 8. The Random forest model fit

Variables	Coefficient
SGI	18.518
SGAI	14.038
TATA	20.504
GMI	13.153
DSRI	34.579
LVGI	11.499
DEPI	62.424
AQI	9.354

According to table 8, the fitted random forest model, the regression coefficients are shown in Table 8, and the developed model is as follows:

$$MScore1 = 18.518SGI + 14.038SGAI + 20.504TATA + 13.153GMI + 34.579DSRI + 11.499LVGI + 62.424DEPI + 9.354AQI$$

Accuracy of the model presented in Table 9:

Table 9. The Accuracy fitting of the random forest model

Beneish model	Accuracy
0	63 %
1	99.98 %

According to table 9, The accuracy of random forest is 99.98 percent.

In continuation, three models are fitted for developed Beneish.

4.3. Developed Beneish -Vector Machin

In Table 10, the Beneish method is used to predict fraud using significant independent variables, and how they are entered is prioritized.

Table 10. The Vector Machine Method

Variables	Coefficient	Priority
DSRI	-43.964	First
GMI	43.513	Second
AQI	39.315	Fourth
SGI	-41.670	Third
DEPI	35.329	Fifth
TATA	-26.985	Seventh
LVGI	-34.794	Sixth
SGAI	-21.392	Eights
INF	-12.526	Ninth
GDP	-1.569	Twelve
EX	-12.339	Tenth
GROW	3.675	Eleventh

According to Table 10, the fitted vector machine model, the regression coefficients estimated, and the estimated fraud model are as follows:

$$\begin{aligned} MScore1 = & -41.670SGI - 21.392SGAI - 26.985TATA + 43.513GMI - 43.964DSRI \\ & - 34.794LVGI + 35.329DSRI - 12.339EX + 39.315AQI - 12.526INF \\ & - 12.339GROW - 1.569GD \end{aligned}$$

Accuracy of the model presented in Table 11:

Table 11. The Accuracy of Vector Machine Model

Beneish model	Accuracy
0	24 %
1	99.91 %
Total	93.62 %

The accuracy of the Vector Machine Method is 93.62 percent.

4.3.1. Developed Beneish –Neural Network Model

As shown in Table 12, 70.1% of the data equivalent to 846 were used as training samples, and 29.9% of the data equivalent to 360 was used as testing samples.

Table 12. Assigning the number of samples

		N	Percent
Sample	Training	846	70.1%
	Testing	360	29.9%
Valid		1206	100.0%
Excluded		45	
Total		1251	

According to table 13, The amount of error obtained from the fit of this model is equal to 23.347 in the training sample, and the amount of error obtained in the testing sample is equal to 12.474. Since the amount of error obtained in the testing sample is less than in the training sample, the model fit is acceptable.

Table 13. The model fit error samples

Training	23.347
Testing	12.474

The effect of independent variables on entering the model is as Table 14:

Table 14. The Neural network model variables

Variables	Coefficient	Priority
DSRI	0.141	Fourth
GMI	0.145	Second
AQI	0.050	Eights
SGI	0.144	Third
DEPI	0.170	First
SGAI	0.084	Sixth
TATA	0.070	Seventh
LVGI	0.103	Fifth
INF	0.013	Twelve
GDP	0.022	Tenth
EX	0.019	Eleventh
GROW	0.040	Ninth

According to table 14, the fitted random forest model, the regression coefficients are shown in the Table, and the developed model is as follows:

$$MScore1 = 0.144SGI + 0.084SGAI + 0.070TATA + 0.145GMI + 0.141DSRI + 0.103LVGI + 0.170DEPI + 0.019EX + 0.050AQI + 0.013INF + 0.040GROW + 0.022GDP$$

Accuracy of the model presented in table 15: **Testing Training**

Table 15. The Accuracy of Neural network

Testing	Accuracy	Training	Accuracy
0	59%	0	63.6 %
1	99.9 %	1	98.2 %
Total	96.1 %	Total	96.1 %

As shown in table 15, the accuracy of the Neural network method is 96.1 percent.

4.3.2. Developed Beneish –Random Forest Model

Table 16 uses the random forest method to detect fraud using significant independent variables and prioritize how they are entered.

Table 16. The random forest coefficients

Variable	Coefficient
DEPI	50.914
DSRI	32.873
TATA	17.606
SGI	17.236
SGAI	13.674
GMI	11.516
LVGI	9.033
EX	8.169
AQI	7.794
INF	7.691
GROW	2.916
GDP	1.936

According to Table 16, the fitted random forest model, the regression coefficients estimated in the table, and the estimated model of fraud detection are as follows:

$$MScore1 = 17.236SGI + 13.674SGAI + 17.606TATA + 11.516GMI + 32.873DSRI + 9.033LVGI + 59.914DEPI + 8.169EX + 7.794AQI + 7.691INF + 2.916GROW + 1.936GDP$$

Table 17. The Accuracy of random forest Model

Beneish Model	Accuracy
0	62 percent
1	99.98 percent
Total	99.96 percent

According to Table 17, the accuracy of the random forest method is 99.96 percent.

4.4. Comparison between Beneish model and developed Beneish

A comparison between the Beneish model and the developed Beneish is shown in table 18.

Table 18. The Comparison between the Beneish model and the developed Beneish

Model	Neural Network	Random Forest	Vector Machine
Beneish	93.7	99.96	93.03
Developed Beneish	96.1	99.96	93.62

According to Table 18, the developed Beneish model with neural network method, random forest, and vector machine has more accuracy than the Beneish model.

5. Conclusions

Given that there is no other source for predicting fraud in the Iranian environment other than financial statements, this study uses the variables of financial statements and develops the Beneish model using audit variables to investigate possible potential fraud. Predicting fraud is how investment opportunities can be properly applied to maximize firm value. Second, the investor can distinguish favorable investment opportunities from unfavorable ones, in which forecasting models show their importance. According to the issues above, the present study seeks to answer whether the Beneish model has been completely successful in identifying fraud in Iranian companies and whether it is possible to improve the model by adding variables. To achieve the objectives of the research and to answer the research questions, after calculating the descriptive statistics of the identified indicators such as mean, and standard deviation, the Beneish model for predicting fraud detection, was developed by 3 neural networks (96.1% accuracy), random forest (99.96% accuracy) and vector machine (93.61% accuracy). In addition, the developed model with neural network method, random forest, and vector machine is more accurate than the basic Beneish model. Finally, considering that the research results show that economic variables can improve the strength of the financial statements fraud model, it is recommended that investors and capital market participants pay attention in their analysis of financial statement fraud to economic variables. Financial analysts and investors may be aware that financial statements may be misleading during economic factors fluctuations. Lawmakers can pay attention to economic fluctuation to improve capital market laws. In addition, because the accuracy of the fitted random forest model is higher than other models, it is suggested that the coefficients obtained from this model be used to investigate fraud in financial statements. Finally, it is suggested that future researchers consider other factors in developing fraud prediction using other fitting models.

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