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Prediction of Stock Performance on the Ghana Stock Exchange Using Financial Ratios: A Logistic Regression Approach

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ABSTRACT : This paper examines the efficacy of financial ratios as predictors of stock performances of 20 selected companies listed on the Ghana Stock Exchange Composite Index (GSE-CI) over a three year period. Stock portfolio selection is one of the biggest challenges faced by market players when investing on the stock exchange. This study uses binary logistic regression with various financial ratios as the explanatory variables to investigate indicators that significantly influence the performance of stocks actively traded on the Ghana Stock Exchange-Composite Index (GSE-CI). Potential performance of a stock on the Exchange is invaluable information to an investor. The study showed that using financial ratios, companies' annual performance on the GSE-CI can be predicted with a 70% level of accuracy into two categories – "good" or "poor" – based on whether or not that particular company outperforms the GSE-CI. This paper maintains that the model developed can enhance the stock performance forecasting ability of investors

Keywords: Financial Ratios, Logistic regression, Stock Performance, Ghana Stock Exchange-Composite Index (GSE-CI), Index Benchmarking.

1. INTRODUCTION

Can data help predict future economic activity? The future, like any multifaceted problem, has far too many variables to be forecasted with certainty. Quantitative and qualitative models, economic models, even psychological models have all been tried — and have all proven futile in predicting the future with certainty. For instance, we believe that models that have accurately predicted the future in the past are likely to predict the future going forward. But that is no more true than believing that a coin will land heads up just because it was accurately predicted it would do so the last twenty times.

Stock Investment can be a huge economic propeller, but it has been observed that most Ghanaians shudder investments due to the perceived high volatility of returns of companies listed on the market. Prediction of the movement of stock returns with some high level of accuracy is therefore crucial to solving this problem. Stock performance prediction models abound in literature. This paper illustrates a simple forecasting model to help distinguish potentially poor performing companies from the good, in order for investors to make better and pre-informed investment decisions.

This paper sought to fit a logistic regression model to predict whether a stock would outperform the market (Ghana Stock Exchange) in a given year using financial ratios. Financial ratios that significantly influence the performance of a stock on the Ghana Stock Exchange Composite Index (GSE-CI) were also investigated. Some model diagnostics were used to determine the adequacy of the model we used for predicting the stock performance.

The applicability of the study is tested by the use of the model in practice for selecting those stocks that offer relatively higher performance. In order to achieve this goal a sample consisting of firms listed on the Ghana

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Stock Exchange Composite Index (GSE-CI) between the years 2007 and 2011, was created and analyzed using the binary logistic regression with the help of a VB.NET application.

2. MATERIALS AND METHOD

In this study, 20 out of the 37 companies listed on the Ghana Stock Exchange were studied for three years; 2011, 2012, and 2013. The relationship between the performance of these 20 companies and some carefully selected financial ratios were examined for those three years. A binary logistic regression model was fitted to explain the relationship between stock performance and these financial ratios. Data was primarily collected from the Ghana Stock Exchange website (www.gse.gov.gh), and from the annual financial statements of the 20 companies randomly selected for this study

2.1 Index Benchmarking

This study incorporates the Index Benchmarking technique for evaluating stock performance. A benchmark index gives a point of reference to investors for evaluating the performance of stocks on a risk-adjusted basis.[5] The Ghana Stock Exchange-Composite Index (GSE-CI) was chosen as the benchmark for this study. Companies were then classified into two categories. Companies whose risk-adjusted return on stock exceeded that of market were classified as 'GOOD' performance companies. However, companies who recorded relatively low risk-adjusted returns as compared to the market were classified as 'POOR' performance companies.

$$\mathrm{R_i} = \text{stock Return} = \frac{\text{change in Price} + \text{Dividend}}{\text{Initial Price}}$$

$$\mathrm{R_i} = \frac{(\mathrm{P_t} - \mathrm{P_{t-1}}) + \mathrm{D_0}}{\mathrm{P_{t-1}}} \qquad (\mathbf{1})$$

$$\text{Market Return} = \sum_{i=1}^{n} \mathrm{w_i R_i} \qquad (\mathbf{2})$$

$$\text{Risk-adjusted return} = RFR + \frac{\sigma_m}{\sigma_i}(\mathrm{R_i} - RFR) \qquad \mathbf{(3)}$$

Where $\mathrm{P_t}$ is the current year-end close stock price

$\mathrm{P_{t-1}}$ is the previous year-end close price

$\mathrm{D_0}$ is the previous annual dividend

$\mathrm{w_i}$ refers to the weight assigned to each stock based on their market capitalisation.

σ_m is the risk of the market (in this case the GSE-CI)

σ_i is the risk of the individual asset $and\ RFR$ is the risk-free rate.

2.2 Featured Financial Ratios

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Financial ratios were chosen as regressors for the model because

1. Financial ratios are easy to compute and a good tool for comparison among the listed companies.
2. Using the risk-adjusted return allowed for a direct comparison of performance meant that a comparison between the returns of individual stocks, and also a direct comparison between an individual stock and the market (benchmark). As result, it was necessary to use data that gives a fair reflection of the factors that can cause a change in the share price, and also influence the level of the earnings/profits (the account from which dividends are paid).[7]

Some of these factors are:

- Investors' expectations of the company's potential earnings.
- Company's management ability
- Investors' expectation of a change in share price.

Financial Ratio	Formula
Earnings per Share	Net Earnings / Number of Outstanding Shares
Price Earnings Ratio	Current Stock Price / Earnings Per Share
Price-Book Value per Share	Stock Price / Book Value Per Share
Percentage Change in Net Sales	Change in Net Sales / Previous Net Sales
Profit Before Tax/Sales	Profit Before Tax/Sales
Asset Turnover Ratio	Revenue / Total Assets
Book Value per Share	(Shareholders' Equity − Preferred Shares) / Total Number of Outstanding Shares

1.3 The Binary Logistic Regression Model (LR)

Classification methods exist in wide varieties in literature and application, among which are Bayes Classifier, K-Nearest, Neighbour, Decision Trees[1].The Binary LR, invariably, is an enhancement of linear regression used to predict an outcome or generate a valuation from a set of independent variables. The model best suits situations where the dependent variable is dichotomous or where the relationship between the independent and dependent variables is not always a straight line, so a non-linear or logistic regression is used.[3] One advantage of the Binary LR is that, through the introduction of an appropriate link function to the linear regression model, the variables need not necessarily follow the normal distribution and may either be continuous or discrete or any combination of both data types.[4] It is most relevant when the dataset is very large, and the independent variables do not follow an orderly way, or obey the assumptions required of discriminant analysis.[3,5] Logistic Regression analysis does not necessarily require the restrictive assumptions concerning the normality distribution of predictor variables and regarding the prior probabilities of failure nor equal dispersion matrices.

In essence, the LR model predicts the *logit* of Y from X.The *logit* is the natural logarithm of the odds ratio.[6] The odds ratio is given by the ratio of the probability of a case (that is, company outperforming the GSE-CI), $\pi(x_i)$ to the probability of a non-case (that is, company under-performing the GSE-CI), $1 - \pi(x_i)$.

The simplest logistic regression model is represented by equation 3

$$logit(Y) = \ln\left(\frac{\pi(x_i)}{1-\pi(x_i)}\right) = \beta_0 + \beta_1 X \qquad (\mathbf{4})$$

Where β_1 is the regression coefficient of X, and β_0 is the Y-intercept. Taking the antilog of equation 3 on both sides, one derives equation 4 to predict the probability of the occurrence of the outcome of interest (that is , the probability of the stock outperforming the market).[6]

$$\pi(x_i) = \frac{exp^{(\beta_0+\beta_1 X)}}{1+exp^{(\beta_0+\beta_1 X)}} \qquad (\mathbf{5})$$

According to equation 3 the relationship between $logit(Y)$ and X is linear. Yet, according to equation 4, the relationship between the probability of Y and X is nonlinear. For that reason, the natural log transformation of the odds in equation 3 is necessary to make the relationship between a categorical outcome variable and its predictor (s) linear. Extending the logic of the simple LR to multiple predictors generates equations 6 and 7.

$$\ln\left(\frac{\pi(x_i)}{1-\pi(x_i)}\right) = logit[\pi(x_i)] = \boldsymbol{X^T\beta} \qquad (\mathbf{6})$$

$$\boldsymbol{X^T\beta} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{k-1}x_{k-1}$$

Where $x_1, x_2, \ldots\ x_{k-1}$ are the independent variables, and $\beta_i\ (for\ i = 1,2,\ldots,k-1)$ are the coefficients of the k respective independent variables and β_0 is the coefficient of the first term, such that k = 1,2,3,....

Therefore,

$$\pi(x_i) = P(Y = Outcome\ of\ interest|X = x_1, X = x_2, \ldots, X = x_{k-1})$$

$$\pi(x_i) = \frac{exp^{(\boldsymbol{X^T\beta})}}{1+exp^{(\boldsymbol{X^T\beta})}} \qquad (\mathbf{7})$$

Typically, the $\beta_0, \beta_1, \ldots, \beta_{k-1}$ are estimated using the maximum likelihood estimation method.

2. RESULTS AND ANALYSIS

The study used the LR technique to develop a model to predict stock performance by classifying companies into two categories, and using financial ratios as predictors. Financial ratios of the 20 selected companies for the years 2011, 2012 and 2013 of the selected companies were used as the independent variables. Using the Index Benchmarking technique afore-mentioned, companies were classified as ‘GOOD’ or ‘POOR’ performance companies by comparing their risk-adjusted stock returns to the market returns for each of the three years.

Performance of Company (based on the market return)	Description	Encoding = perf
GOOD	Risk-Adjusted Stock Return Above Market Return	1
POOR	Risk-Adjusted Stock Below Market Return	0

Table 2.1: Dependent Variables

Variable Name	Description
ns	Percentage change in Net Sales
eps	Earnings per Share
pbts	Profit before Interest and tax / Sales
atr	Asset Turnover Ratio
pe	Price/Earnings Ratio
bv	Book Value
pbv	Price/Book Value per

Table 3.2: The Independent Variables

2.1 Empirical Results and Analysis

After analyzing the data using the SPSS statistical tool, the estimated logistic regression model for predicting the stock performance using the financial ratios as the predictors is given by:

$$perf = -0.534 + 1.119\boldsymbol{eps} + 1.906\boldsymbol{pbts} - 0.14\boldsymbol{atr} + 0.012\boldsymbol{pe} - 0.016\boldsymbol{bv} - 0.078\boldsymbol{pbv} + 0.259\boldsymbol{ns}$$

Where $perf = \ln\left(\frac{\pi(x_i)}{1-\pi(x_i)}\right),\ \ and\ \ \pi(x_i) = \frac{\exp(perf)}{1+\exp(perf)}$

In the above equation, it is possible to predict the performance of a particular stock given the relevant financial ratios as used in the model, by computing the values, $perf\ and\ \pi(x_i)$. In the observed data, the proportion of 'good' performance was 0.5. Therefore if the computed $\pi(x_i)$ is greater than 0.5 then the stock can be classified as good, or would perform well on the GSE-CI. On the other hand, a $\pi(x_i)$ less than 0.5 implies that the stock would perform poorly on the GSE-CI. A summary of the model is given by the table below.

2.2 Model Interpretation

Table 2.3: Predicted Logistic Regression Model

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Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	ns	.098	1.032	.009	1	.925	1.103
	eps	2.388	1.488	2.575	1	.0109	10.887
	pbts	1.069	1.925	.309	1	.579	2.913
	atr	-.603	.515	1.370	1	.242	.547
	pe	-.064	.055	1.332	1	.248	.938
	bv	-.774	.526	2.163	1	.141	.461
	pbv	.374	.236	2.503	1	.114	1.454
	Constant	.458	1.083	.179	1	.672	1.581

a. Variable(s) entered on step 1: ns, eps, pbts, atr, pe, bv, pbv.

The equation for the fitted model is given by:

$$perf = \ln\left(\frac{\pi(x_i)}{1-\pi(x_i)}\right)$$
$$= 0.458 + 0.098\boldsymbol{ns} + 2.388\boldsymbol{eps} + 1.\mathbf{069}\boldsymbol{pbts} - 0.603\boldsymbol{atr} - \ 0.064\boldsymbol{pe} - 0.774\boldsymbol{bv} + 0.374\boldsymbol{pbv}$$

Wald statistic was used to test the significance of the coefficients of the regression function variables. Like the null hypothesis in the analysis of the significance of coefficients in linear regression, here the null hypothesis is that the respective explanatory variable had no impact on the response variable. Table 2.3 shows that Wald statistic for Earnings Per Share (**eps**) is less than 0.05 meaning that the null hypothesis is rejected; therefore, the coefficients were significant.

The Wald Statistic provides the statistical significance of each estimated coefficient. If the logistic coefficient is statistically significant, we can interpret it in terms of how it impacts the estimated probability and thus the prediction of group membership.[9] Several authors have identified problems with the use of the Wald statistic.

2.3 Model Diagnostics

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	14.058	7	.005
	Block	14.058	7	.005
	Model	14.058	7	. 005

Table 2.4: Omnibus Tests of Model Coefficient

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The model chi-square value which is the difference between the null model and the current (full) (chi-square values =14.058). For this test, we reject the null hypothesis since the p-value (sig. value in Table 2.4) is less than 0.05 (significance level), implying that the addition of the independent variables improved the predictive power of the model. The block and the step vales are equal to the model values since all values were entered at the same time. The omnibus tests are the measures of how well the model performs. They test whether the explained variance in a set of data is significantly greater than the unexplained variance, overall.[4] However, there can be legitimate significant effects within a model even if the Omnibus test is not significant.[6,9]

Hosmer-Lemeshow Test

The Hosmer-Lemeshow test as shown in **Table 2.5** explores whether the predicted probabilities are the same as the observed probabilities. An overall goodness of fit of
the model is indicated by p-values > 0.05 (Hosmer and Lemeshow, 2000). This model produced an insignificant difference between the observed and predicted probabilities indicating a good model fit.[8]

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.924	8	.545

Table 2.5: Hosmer and Lemeshow Test

Model Predictive Power

A classification table which indicates how well the model predicts cases to the two dependent variable categories displayed in **Table 2.6**. The following classification table helps to assess the performance of the model by cross-tabulating the observed response categories with the predicted response categories.[9]

For each case, the predicted response is the category treated as 1, if that category's predicted probability is greater than the user-specified cut-off. The cut-off value is taken at 0.5

Table 2.6: Classification Table

Classification Table[a]

Observed			Predicted		
			perf		Percentage Correct
			0	1	
Step 1	perf	0	17	13	56.7
		1	5	25	83.3
	Overall Percentage				70.0

a. The cut value is .500

This table shows the comparison of the observed and the predicted performance of the companies and the degree of their prediction accuracy. It also shows the degree of success of the classification for this sample. The number and percentage of cases correctly classified and misclassified are displayed. It is clear from this table that the poor companies have a 56.7% correct classification rate, whereas good companies have a 83.3% correct classification rate. Overall, correct classification was observed in 70.0% of original grouped cases. With regard to Table 2.6, type one error (when a poor-performing firm is mistakenly classified as a good-performing firm) is 16.7% (1-sensitivity coefficient), and type two error (when a good-performing firm is mistakenly classified as a poor-performing firm) is 43.3% (1-specificity coefficient).

3. CONCLUSION AND RECOMMENDATIONS

This study showed that using financial ratios such as the earnings per share, the price-earnings ratio, the percentage change in net sales, book value per share, price-book value per share, profit before tax-sales ratio and the asset turnover ratio, the performance of stock on risk-adjusted basis (with the market as a base) can be fairly predicted with 70% accuracy.

The analysis of the significance of the coefficients of the independent variables was done using the Wald test. It was established that among the seven financial ratios used, none of them was significant in predicting whether a stock would outperform the market or not. However the omnibus test showed that the predictive ability of the model improves significantly with the addition of the other financial ratios.

It is recommended that since only one of the ratios, the earnings per share, significantly affects the performance of a stock. Investors are encouraged to choose companies with higher earnings per share.

Also, considering the absence of relevant information on the companies listed on the GSE-CI, authorities concerned should endeavour to make available such information. This is because such information can be very helpful to academic researchers for future analysis.

During the data collection process, it was realized that the financial statements available for some companies were done by different independent auditors for the three-year period that was being studied. There were also some currency disparities as some companies opted to keep their records in foreign currencies such as the dollar. This created serious inconsistencies, and as such leading to different audit figures on the same company. It is therefore recommend that an institutionalized system be put in place, where such auditing process would be done by a single body and in the local currency.

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APPENDICES

Appendix A

Input Data set for Independent Variables

YEAR	TRADING NAME	ns	eps	pbts	atr	pe	bv	pbv
2011	AGA	0.26	0.402	0.3531	1.3405	3.0	2.7103	1.25
2012	AGA	-0.04	0.215	0.1765	1.21	8.0	2.8550	1.3
2013	AGA	-0.14	-0.562	-0.4437	1.84	5.0	1.8580	2.01
2011	AYRTN	0.61	0.0133	0.2023	1.18	11.0	0.0800	2.15

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2012	AYRTN	0.15	0.0155	0.1362	1.2	19.0	0.0900	2.01
2013	AYRTN	0.05	0.0016	0.0425	1.25	20.0	0.09	2.01
2011	BOPP	0.8	0.2754	0.2808	0.3309	5.0	0.85	1.24
2012	BOPP	0.17	0.3852	0.3358	1.01	3.0	1.16	1.2
2013	BOPP	-0.13	0.1668	0.173	0.81	18.0	1.25	2.56
2011	CAL	0.09	0.0681	0.308	0.8581	5.0	0.36	0.7
2012	CAL	0.92	0.0942	0.489	0.7022	5.0	0.38	1.0
2013	CAL	0.83	0.1706	0.4784	0.93	6.0	0.52	1.87
2011	EBG	0.2	0.31	0.6189	0.6494	9.0	1.14	2.8
2012	EBG	1.07	0.45	0.527	0.77	7.0	1.56	1.9
2013	EBG	0.34	0.65	0.4026	0.84	10.0	1.91	2.93
2011	ETI	0.26	0.176	0.3158	0.6	5.0	0.24	0.42
2012	ETI	0.54	0.17	0.25656	0.63	5.0	0.27	0.44
2013	ETI	0.19	0.6	0.1386	0.75	4.0	0.27	0.67
2011	EGL	0.4046	0.145	0.2647	1.27	13.0	0.59	0.65
2012	EGL	1.15	0.148	1.1891	0.26	5.0	0.83	0.58
2013	EGL	1.36	0.238	0.3534	0.48	5.0	1.04	1.8
2011	FML	0.05	0.16	0.2311	1.75	17.0	0.53	4.53
2012	FML	0.35	0.23	0.2475	2.39	15.0	0.52	6.83
2013	FML	-0.06	0.19	0.2142	1.82	31.0	0.66	10.03
2011	GCB	-0.34	0.07	0.1211	1.44	10.0	0.67	2.75
2012	GCB	0.47	0.54	0.5128	1.27	5.0	1.11	1.88
2013	GCB	0.47	0.86	0.5743	1.18	7.0	1.76	2.79
2011	GOIL	0.31	0.038	0.0169	16.72	7.0	0.19	1.68
2012	GOIL	0.2800	0.045	0.0165	18.31	12.0	0.22	2.73
2013	GOIL	0.2600	0.055	0.0172	18.25	16.0	0.24	3.78
2011	GGBL	0.1800	0.0030	0.0019	5.35	27.0	0.22	6.98

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2012	GGBL	0.2000	0.133	0.1136	2.1	30.0	0.66	3.98
2013	GGBL	0.1000	0.086	0.0868	2.1	29.0	0.72	8.44
2011	HFC	0.0800	0.0592	0.2453	0.76	11.0	0.42	1.07
2012	HFC	0.1700	0.079	0.2736	0.52	10.0	0.44	1.0
2013	HFC	0.7400	0.1327	0.434	0.69	9.0	0.58	1.65
2011	MLC	0.1900	0.0636	0.1164	1.94	2.0	0.35	0.29
2012	MLC	0.3900	0.1241	0.1657	1.17	3.0	0.8	0.19
2013	MLC	-0.1800	-0.021	-0.038	1.0	11.0	0.77	0.5
2011	PBC	1.0600	0.0576	0.0288	27.48	4.0	0.1	2.53
2012	PBC	0.7900	0.021	0.0118	23.77	5.0	0.1	1.78
2013	PBC	-0.030	0.0184	-0.0097	28.42	6.0	0.08	2.06
2011	PZC	0.21	0.226	0.1144	2.12	11.0	0.16	5.34
2012	PZC	0.24	0.0063	0.0075	2.63	6.0	0.19	0.37
2013	PZC	0.16	0.0468	0.1046	2.44	8.0	0.23	3.39
2011	SIC	0.24	0.24	0.0942	0.93	7.0	0.38	1.05
2012	SIC	0.24	0.05	0.0196	1.33	8.0	0.44	0.77
2013	SIC	0.0	-0.008	0.0113	1.22	17.0	0.41	0.95
2011	TOTAL	0.32	1.6135	0.0318	13.383	13.0	5.19	3.82
2012	TOTAL	0.2800	2.1829	0.0328	14.4525	10.0	6.16	3.82
2013	TOTAL	0.0110	0.3233	0.0356	12.22	14.0	0.92	5.43
2011	TLW	1.11	1.44	0.4656	0.48	42.0	1.055	2.94
2012	TLW	0.27	1.36	0.476	0.44	17.0	1.174	3.24
2013	TLW	0.13	0.36	0.1183	0.49	24.0	1.44	2.43
2011	UNIL	0.33	0.4818	0.1387	4.89	14.0	0.78	8.48
2012	UNIL	0.18	0.2573	0.0736	8.88	28.0	0.51	1.68
2013	UNIL	0.15	0.2252	0.0581	9.91	47.0	0.52	3.50

2011	UTB	0.34	0.04	0.1732	1.63	8.0	0.2	1.58
2012	UTB	0.34	0.34	0.1991	1.04	9.0	0.28	1.31
2013	UTB	0.4	0.4	0.0714	1.46	9.0	0.28	1.56

Appendix B

Source code for the embedded vb.net application

```
Dim eps As Double
    Dim pbts As Double
    Dim atr As Double
    Dim pe As Double
    Dim bv As Double
    Dim pbv As Double
    Dim ns As Double
    Dim Result1 As Double
    Dim Result2 As Double
    Dim Operand1 As Double



    Private Sub btnlog_Click(sender As Object, e As EventArgs) Handles btnlog.Click
        eps = tb1.Text
        pbts = tb2.Text
        atr = tb3.Text
        pe = tb4.Text
        bv = tb5.Text
        pbv = tb6.Text
        ns = tb7.Text
        Result1 = 0.458 + (0.098 * ns) + (2.388 * eps) - (1.069 * pbts) - (0.603 * atr) - (0.064 *
pe) - (0.077 * bv) + (0.374 * pbv)
        lblDisp1.Text = Result1

    End Sub

    Private Sub Button1_Click(sender As Object, e As EventArgs) Handles Button1.Click
        tb1.Text = ""
        tb2.Text = ""
        tb3.Text = ""
        tb4.Text = ""
        tb5.Text = ""
        tb6.Text = ""
        tb7.Text = ""
        lblDisp1.Text = ""
        lblDisp2.Text = ""
        lblDisp3.Text = ""
    End Sub

    Private Sub btnodd_Click(sender As Object, e As EventArgs) Handles btnodd.Click
        Operand1 = Convert.ToDouble(lblDisp1.Text)
        Result2 = Math.Exp(Operand1) / (1 + Math.Exp(Operand1))
        lblDisp2.Text = Result2
    End Sub

    Private Sub btndec_Click(sender As Object, e As EventArgs) Handles btndec.Click
        If lblDisp2.Text >= 0.50 Then
            lblDisp3.Text = "GOOD"
```

DOI: 10.18535/ijsrm/v4i6.13

```
        Else
            lblDisp3.Text = "POOR"
        End If
    End Sub

    Private Sub Label1_Click(sender As Object, e As EventArgs) Handles Label1.Click

    End Sub

    Private Sub Label7_Click(sender As Object, e As EventArgs) Handles Label7.Click

    End Sub
End Class
```

Graphical Interface of Visual Basic Application for Model Illustration