Data Science in Finance and Economics

DSFE, 1(3): 215–234.
DOI: 10.3934/DSFE.2021012
Received: 05 October 2021
Accepted: 19 October 2021
Published: 29 October 2021

http://www.aimspress.com/journal/dsfe

*Research article*

# The usage of logistic regression and artificial neural networks for evaluation and predicting property-liability insurers' solvency in Egypt

**Hassan Eid Elghaly[1, 2,*] and Zhang Diping[1]**

[1] School of Science, Zhejiang University of Science and Technology, Hangzhou 310023, China
[2] Department of Applied Statistics and Insurance, Faculty of Commerce, Mansoura University, Mansoura 35516, Egypt

* **Correspondence:** Email: hassanghaly@mans.edu.eg; Tel: +201555522542.

**Abstract:** Unlike prior solvency prediction studies conducted in Egypt, this study aims to set up a real picture of companies' financial performance in the Egyptian insurance market. Therefore, 11 financial ratios commonly used by NAIC, AM BEST Company, and S&P Global Ratings were calculated for all property-liability insurance companies in Egypt from 2010 to 2020. They have been used to measure those companies' financial performance efficiency levels by comparing these ratios with the international standard limits. The financial analysis results for those companies revealed that property-liability insurers in Egypt do not have the same level of financial performance efficiency where those companies are classified into three groups: excellent, good, and poor. Furthermore, this paper investigates using the stepwise logistic regression model to determine the most factors among these selected financial ratios that influence those companies' financial performance. The results suggest that only three ratios were statistically significant predictors: "Risk retention rate", "Insurance account receivable to total assets", and "Net profit after tax to total assets". Finally, this paper presents the multi-layers artificial neural network with a backpropagation algorithm as a new solvency prediction model with perfect classifying accuracy of 100%. The trained ANN could predict the next fiscal year with a prediction accuracy of 91.67%, and this percent is a good and favorable result comparing to other solvency prediction models used in Egypt.

**Keywords:** stepwise logistic regression; multi-layers artificial neural network; classification; solvency; financial ratios; property-liability; the Egyptian insurance market

**JEL Codes:** C45, G22, N27

## 1. Introduction

Academically studies predicting solvency became common in previous accounting and finance studies during the past two centuries, but there was little interest in predicting it in the insurance industry (Burca and Batrinca, 2014). However, most empirical studies examined the effect of early warning tests, Best's Rating, and the NAIC'S IRIS using actual data and comparing actual insolvency with expected results. For instance, Pottier and Sommer (2002) indicated that early warning system measurers produced by A.M. Best provide more predictive power than those produced by the National Association of Insurance Commissioners (NAIC); NAIC's RBC is an unwell predictor of solvency (during the period 1995–1998). The study of Brockett et al. (2006) found that both FAST and RBC variables in general performed less well than expected relative to other data sets and variables.

Historically, the prediction models and methods of solvency are continuously developing. Scholars have used and applied various techniques and models to predict insurance companies' solvency. This development has been started with the traditional statistical methods, the nonparametric methods such as binary logit regression (BLR) and discriminant analysis (DA) and has been ended with artificial intelligence and machine learning algorithm (Gross and Vozikis, 2000). The recent studies' Findings that used the artificial neural network for solvency prediction have put researchers applied the traditional mathematical–statistical methods in serious challenges (Virág and Kristóf, 2005). Artificial neural networks started to be well accepted in the 1980s in both the academic literature and practice. This family of prediction methods has found an answer to several problems also found their way to solvency prediction with high power of prediction (Kristóf, 2004). Recent previous solvency literature pointed out that ANNs yield a more reliable prediction method than discriminant analysis and logistic regression analysis (Atiya, 2001; Back et al., 1996; Ooghe et al., 1999).

There is a fair number of prior literature focused on solvency in insurance companies and its influencing factors, both internal and external using different methods and models for solvency prediction such as Univariate discriminant analysis (UDA), Multivariate discriminant analysis (MDA), Logistic regression (LR), Recursive partitioning model (RPM), Cascaded regression (CR), nonlinear spline models (NSM) and Nonparametric methods (NPM). (Zhang and Nielson, 2015). Among those who used the UDA, we can mention the study of Beaver (1966) which applied this analysis in 158 firms and found the cash flow to total debt ratio was the best choice of financial indicators for solvency prediction.

While the Univariate discriminant analysis used a single financial ratio, the multivariate discriminant analysis included more than one financial ratio from the most notable financial indicators measuring profitability, liquidity, and solvency (Huang and Wang, 2012). Using this method, Altman (1968) presented a powerful insolvency model for 33 pairs of solvent/insolvent companies and five financial ratios, with 95% accuracy in predicting insolvency one year before. Trieschmann and Pinches (1973) also conducted MDA to classify 42 out of 52 insurance companies into two groups (solvent or insolvent). Altman, Haldeman, and Narayanan (1977) re-used the MDA by developing their seven variable ZETA model for 58 solvent and 53 insolvent firms. In a word, Multivariate discriminant analysis was the empirical method employed in these studies (Pinches and Trieschmann, 1974; BarNiv, and Hershbarger, 1990; BarNiv and McDonald, 1992; Carson and Hoyt, 1995; Brockett et al., 2006; Hsiao and Whang, 2009; Altman et al., 2020).

However, according to (Ohlson, 1980) MDA had an overstated power of predictive and indicated that the shortcomings of this methodology largely came from its hypotheses. This study conducted the maximum like-lihood estimation method of the so-called conditional logit model. In reaction to its problems, other models were developed, such as Logistic regression. The following studies applied LR in the solvency prediction. (BarNiv and Hershbarger, 1990; BarNiv and McDonald, 1992; Carson and Hoyt, 1995, 2000; Lee and Urrutia, 1996; Cummins et al., 1999; Pottier and Sommer, 2002, 2011; Cheng and Wong, 2004; Brockett et al., 2006; Sharpe and Stadnik, 2007; Hsiao and Whang, 2009; Cheng and Weiss, 2012; Zhang and Nielson, 2015; Altman et al., 2020).

In addition to these three models, other studies applied different models such as the Recursive partitioning model (Carson and Hoyt, 1995) and nonlinear spline models (Baranoff et al., 2000). There are many comparative studies among the MDA, LR, and the nonparametric methods (BarNiv and Hershbarger, 1990; Brockett et al., 1994; Brockett et al., 2006; Huang et al., 1994; Kohonen et al., 1996; Hsiao and Whang, 2009; Affes and Hentati-Kaffel, 2019). Among these comparative studies, BarNiv and Hershbarger (1990) pointed out that the nonparametric analysis and logistic regression models are more efficient than MDA in the solvency prediction. Brockett et al. (2006) did a comparative study among MDA, LR, nonparametric model with Back-Propagation (NPM-BP), and nonparametric model with Learning Vector Quantization (NPM-LVQ) for the prediction of financial hazard in life insurers. They found that the NPM-BP and NPM-LVQ dominated the traditional MDA and LR. To sum up, the recent previous solvency literature pointed out that artificial neural networks yield a more reliable prediction method than discriminant analysis and logistic regression analysis (Atiya, 2001; Back et al., 1996; Ooghe et al., 1999). Therefore, based on these prior studies, this study hopes that the neural network models for solvency prediction will provide a reliable prediction for the Egyptian insurance market.

After reviewing the insurers' solvency literature, we find that both the logistic regression and the neural networks have been used for just prediction purposes. In contrast, this study uses these two models for two variant objectives. We use the logistic regression model for the analysis purpose to determine the most factors that influence insurance companies' solvency in Egypt. At the same time, the authors use neural networks to predict these companies' future solvency. This scenario is different from the existing studies in this field in two respects: on the one hand, solvency analysis literature used multiple regression for the same objective. On the other hand, all prior prediction studies used ANNs with the sigmoid logistic activation function for the output layer. While in this study, we propose the softmax function for the same layer since it showed more accuracy in prediction than the sigmoid logistic used by previous studies. To achieve these two main purposes, the authors put forward the following Specific objectives:

1. To analyze the Egyptian insurance market's solvency according to the actual data for the property and liability companies during the interval 2009/2010–2019/2020.
2. To determine the most factors that influence these companies' solvency using the logistic regression analysis (LR).
3. To predict the solvency of those companies using the artificial neural network (ANN).

## 2. Materials and methods

This study uses the actual data provided in the Egyptian statistical yearbook of the property-liability insurance companies from 2009/2010 to 2019/2020. We include all public and private property-liability insurance companies registered during the study period in the Egyptian insurance market. Since the study focuses on 2010 to 2020, the authors exclude companies that got out of the Egyptian insurance market. Therefore, 12 property-liability insurance companies were determined for this research.

*2.1. Variables*

To set up a real picture of those companies' financial performance in the Egyptian insurance market, 11 financial ratios were calculated for each company compared with the international standard limits. The presence of many indicators used for solvency prediction in the global insurance market and the difference of those indicators from one market to another, the authors' choice of these financial ratios were based on the ratios provided by NAIC S' IRIS and FAST, AM BEST company and S&P Global Ratings. After editing their limits in a manner that conforms to the Egyptian insurance market conditions, the authors calculated these ratios. These ratios shown in Table 1 were used as the independent variables in our empirical analysis.

**Table 1.** The financial ratios and their international standard limits.

| Ratios | Name | Unusual values | |
|---|---|---|---|
| | | Over | Under |
| X1 | Gross Premiums Written to Policyholders' surplus | 400 | |
| X2 | Net Premiums Written to Policyholders' surplus | 200 | |
| X3 | Risk retention rate | | 50 |
| X4 | Technical provision + policyholders' surplus to net premiums written | | 150 |
| X5 | Liabilities to Liquid Assets | 105 | |
| X6 | Technical provisions to liquid assets | 100 | |
| X7 | Insurance account receivable to total assets | 10 | |
| X8 | Investment Yield | | 8 |
| X9 | Net profit after tax to policyholders' surplus | | 5 |
| X10 | Net profit after tax to total assets | | 2 |
| X11 | Technical provisions to policyholders surplus | 350 | |

Source: the authors' preparing table based on the ratios provided by NAIC s' IRIS, FAST, AM BEST company, and S&P global ratings.

2.1.1. Dependent variable

No company has been bankrupt before in the Egyptian insurance market, so the authors classified the companies in this study according to the efficiency level of the financial performance into two categories: troubled (insolvent) and financially stable (solvent). A company with four ratios or more fall outside the usual range will be considered insolvent; otherwise, it will be solvent. It is noted that this classification criterion is adopted by NAIC. Based on this criterion, the dependent variable is binary, and we indicate 1 to solvent companies and 0 to insolvent ones.

*2.2. Binary logistic regression*

For a situation where the dependent variable is binary, Logistic regression is a reliable analysis of identifying which independent variables have the most effect and which can be ignored. The binary logistic is used when the output variable has two categories coded as 1 or 0. Unlike other regression techniques, binary logistic regression does not require the normal distribution for the independent variables, and the linear association between the output and the input variables is not assumed.

However, logistic regression requires the linear relationship between independent variables and log odds (Garson, 2014) as the following Equation:

$$\textbf{Logit}(y) = \textbf{ln}\ (\text{odds}) = \textbf{ln}\ (\frac{p}{1-p}) = \alpha + \beta 1x1 + \cdots + \beta kxk \quad (1)$$

where $P$ is the probability of occurrence, x is the independent variable, and $\beta$i are the model coefficients. The prediction of the probability of occurrence can be calculated by deriving the following Equation from Equation (1):

$$\boldsymbol{p_i} = \frac{\boldsymbol{e^{\alpha+\beta 1x1+\cdots+\beta kxk}}}{\boldsymbol{1+e^{\alpha+\beta 1x1+\cdots+\beta kxk}}} = \frac{\boldsymbol{1}}{\boldsymbol{1+e^{-(\alpha+\beta 1x1+\cdots+\beta kxk)}}} \quad (2)$$

In logistic regression, the maximum likelihood estimation is used to find the model parameters. $\alpha$ and $\beta$ (Menard, 2002; Park, 2013). MLE aims to get the values of the model parameters that maximize the log-likelihood function over the parameter space to make the observed values of the dependent variable most probable given the observed data of the independent variables (Walker, 1996). Stephenson et al. (2008) show that the likelihood function in the case of the logistic regression can be written as follows:

$$L\ (\beta_i) = \prod_{i=1}^{n} p_i^{y_i}(1-\ p_i^{y_i}\ ) \quad (3)$$

After estimation the model coefficients, the next step is to estimate and evaluate the model's fit. The Logistic regression evaluation process includes overall model evaluation, its predictive capacity, and the statistical significance of each independent variable (Hosmer and Lemeshow, 2000; Hair et al., 2009). For the overall model evaluation, the measures which most commonly used to test logistic regression model's fit are −2 log-likelihood, chi-square, Hosmer and Lemeshow test, BIC (Bayesian Information Criterion), Cox & Snell's pseudo $R^2$ of and Nagelkerke's pseudo $R^2$(Fernandes et al., 2021). The −2 log-likelihood ratio compares the null model (without independent variables) with the full model (with the independent variables). Furthermore, it makes an easy comparison among the different models using stepwise methods. The smaller it is, the better the fit of the model. The difference between both −2 log-likelihood ratios is the chi-square statistic. The larger the chi-square, the better the significance of the model.

Similarly, the smaller the BIC (Bayesian Information Criterion) measure fit, the better model's fit. Pseudo $R^2$ is an additional measure commonly used to evaluate the logistic regression similarly to linear regression (Hair et al., 2009). The closer to one, the better is the estimated model. Fernandes et al. (2021) state that a pseudo $R^2$ of 1 indicates a perfect explanation of the variation in the dependent variable by the independent variables. The last measure used as a goodness of fit test for the overall logistic regression model is Hosmer and Lemeshow. The Smaller it is, the better fit the data. In other words, the large values with p-value < 0.05 means a poor fit to the data.

Lastly, a researcher must verify the model's predictive capacity and analyze the significance of each independent variable. The classification table (also known as a confusion table) (Garson, 2011) shows the number of the dependent variable cases that are predicted correctly and those that are not predicted correctly using dichotomized predictions based on a cutoff (ex.: 0.50) and correct high percent indicates that the model has a good fit. However, Garson (2011) suggested that these tables should not be used exclusively as goodness-of-fit measures because they do not use the actually predicted probabilities.

Despite this flexibility, logistic regression is sensitive to some problems such as multicollinearity between the independent variables (Fernandes et al., 2021). Increasing the number of observations or the sample size is a simple way to reduce this problem (Kennedy, 2008). To perform data reduction analysis such as principal components analysis is also an additional option to handle multicollinearity. Quite large sample size is one of the requirements of logistic regression to avoid overestimating the effect measure. Furthermore, the more explanatory variables are included in the model, the larger the sample size is required. Hosmer and Lemeshow (2000) recommend at least a sample size of 400 cases. Hair et al. (2009) suggest that each independent variable has 10 cases. This study applies the Stepwise method as a helpful method to determine which independent variables we need to include in the model and which are not. This method excludes statistically insignificant variables. It will continue elimination until all predictors in the model are statistically significant.

### *2.3. Artificial neural network*

In the mid-twentieth century, a group of neurophysiologists and computer scientists has developed algorithms simulated to the human brain known as artificial neural networks (Choi et al., 2020). It was intended by that algorithm to react with the world in much the same way as does the biological neural networks that constitute the human brain in recognizing objects. (Brockett et al., 1994). Other scientists have since used ANNs to find a solution for many problems that were impossible to solve by traditional computational and statistical techniques. Now ANNs are used in different industries and fields such as medical diagnosis, medicine, chemistry, banking, finance, face identification, signal classification, and so on.

Structurally, ANNs were derived from the architecture of the human brain, which is formed of many neurons. The artificial neural networks are constructed of a set of nodes, which are connected by links. Each link has a weight associated with it. Every node forms an artificial neuron, which has inputs and only one output. The links between nodes represent a connection that passes the output of a given neuron onto another neuron as an input. The neurons are grouped in layers (Were et al., 2015). Neurons of a given layer link only to neurons of the immediately previous and instantly following layers. The purest form of ANNs contains just three layers, namely the input layer, the hidden layer, and the output layer. Each layer has a specific objective. For instance, the input layer picks up the external data and transfers them to the hidden layer, and the output layer produces the result from the hidden layer, which is between the input, and output layers (Krogh, 2008). Artificial neural networks may have one or more hidden layers and sometimes they may have no hidden layer. ANNs work the same way that the real neural networks inside the human brain do (Negnevitsky, 2011). External information flows to the network via the input layer. Each input is randomly assigned weights through the connection they travel along. Every input is multiplied by its weight. The weighted sum after adding a bias to this sum passes to an activation function, described below. This function, in turn, transfers the modified input to the output layer that produces the ultimate output. This data movement is called feed-forward propagation (Berthold and Hand, 2003), and it is different from the backpropagation process, explained below.

As we have covered above, Feedforward means that the data is fed to the input layer, then travels to the hidden layer, and finally to the output layer. In contrast, backward propagation means moving from the right to the left, i.e., from the output layer to the earlier layers in the neural network (Zekić et al., 2016). So to be precise, there is no forward propagation per se, as it is a part of the backward propagation-training algorithm (Krogh, 2008). The idea is that data is fed forward firstly to get the output vector, and then the error is calculated, then propagate backward, updating weights and biases for each layer to minimize the cost function and get the desired output in the output layer. The cost (loss) determines the adjustment level concerning the activation function, weights, and bias (Gschwind, 2007).

### 2.3.1. Activation functions

It is counted as a key part of the neural network layout as it locates what type of role the neural network implements. Activation functions are just used for hidden and output layers. It should be noted that the activation function used in the hidden layer rules how fully the neural network learns the training dataset while it is in the output layer determines the type of predictions that the network can make. A brief description of these activation functions, which are most commonly used in practice for each type of layer in turn, will be given in the following lines. There are many different types of activation functions, but the following are the principal functions used in practice for hidden layers:

A. The Sigmoid logistic

The Sigmoid activation function in machine learning is normally used to refer to the logistic function used in the logistic regression classification algorithm. It takes its name from the Greek letter sigma due to its characteristic curve, which looks like S-shape. One of the most commonly used sigmoid functions is the nonlinear logistic activation function, which converts any real value as input into one output value that can be explained as a probability in the range of 0 to 1. The larger the input value, the closer the output value will be to 1, else the smaller it, the closer the output will be to 0. It is mathematically defined as follows:

$$\boldsymbol{s}(x) = \frac{1}{1+e^{-x}} = \frac{e^{x}}{e^{x}+1} \tag{4}$$

B. Hyperbolic Tangent (Tanh)

Tanh activation function is mathematically calculated as follows;

$$\boldsymbol{f}(\boldsymbol{x}) = \mathbf{tanh}(\boldsymbol{x}) = \frac{(e^{x}-e^{-x})}{(e^{x}+e^{-x})} \tag{5}$$

Similar to the logistic function the more positive the input value, the closer the output value will be to +1, else the more negative it, the closer the output will be to −1. However, in practice, Tanh is usually preferred to logistic for these reasons (Mollahosseini et al., 2016). Firstly, the output value for the hyperbolic tangent function is symmetric around the origin, but it is not that in the logistic function. Thus, the input to each layer will not be of the same sign in the case of Tanh, while it will be the same sign in the case of the logistic function, and this makes the training of the neural network by the logistic function more complex. In addition, using Tanh with its range between −1 to +1 implies that the mean of the hidden layer will be 0 or very close to it, helping in centering the data and makes learning for the next layer much easier as compared to the logistic function. Moreover, using the Tanh function makes the output values easily map as strongly negative, neutral, or strongly positive.

C. Rectified Linear Unit (ReLU)

The rectified linear unit activation function is also called ReLU. It is actually the most common activation function used in neural networks for hidden layers. The ReLU function is given by:

$$\boldsymbol{f}(\boldsymbol{x}) = \max(0, x) \tag{6}$$

Unlike Logistic and Tanh functions, ReLU is much faster to learn and simple to be calculated, less liable to vanishing gradients problems because of its constant gradient of 1, whereas the other previous sigmoid functions have a gradient that quickly converges towards zero and is easy to backpropagate the errors (Ping et al., 2017). Although these advantages of the ReLU activation function, it faces some limitations, such as the dying problem (Maas et al., 2013). It means that some dead neurons never be activated, and this is in the case of the negative input values since its gradient value is zero, which makes the model less able to fit or train from the data properly. The following functions are considered the most widely used for the output layers.

A. Linear function (Identity)

It is just used for output layers and it is perhaps ideal for simple tasks where interpretability is highly desired since the gradient of it is a constant and does not depend on the input x. So it is not possible to use backpropagation, and the network cannot train well and capture the complex patterns from the data (Hara et al., 2017). However, to be precise, it is better than the step binary function, which does not allow multi-value output, and the gradient of the step binary function is zero, so the weights and biases do not update. That is why the non-linear activation function is usually used in deep learning. It has the same Equation and graph of the straight line:

$$\boldsymbol{f}(\boldsymbol{x}) = \boldsymbol{x} \tag{7}$$

B. Sigmoid Logistic

It is described above, and it is used for the hidden and the output layer as well.

C. Softmax

This function is very similar to the previous sigmoid logistic function since it converts any vector of real values as input into an output vector- with the same length- of values that sum to 1.0. These values also can be explained as a probability in the range of 0 to 1, like the case of the logistic function. The only difference is that the Sigmoid is used for binary classification while softmax is used for multi-classification in the Logistic Regression model. In addition, the softmax operates on a vector of k real value, which might be negative, positive, or zero, whereas the sigmoid takes a scalar i.e., it is a kind of Multi-Class Sigmoid. It is also called the softargmax function as it is like the argmax function, which outputs 1 for the maximum option and a 0 for all other options. However, the Softmax function is smoother and softer than the argmax. The softmax function is mathematically calculated as follows:

$$\boldsymbol{\sigma}\overrightarrow{\boldsymbol{Z}_{\boldsymbol{\iota}}} = \frac{\boldsymbol{e}^{\boldsymbol{z}_{\boldsymbol{i}}}}{\sum_{\boldsymbol{j}=\boldsymbol{1}}^{\boldsymbol{k}} \boldsymbol{e}^{\boldsymbol{z}_{\boldsymbol{j}}}} \tag{8}$$

As mentioned above, the softmax activation function is used for the output layer in the neural network for multi-class classification (Szandała, 2021). In this study, the authors used two layers feed-forward neural network with a backpropagation algorithm. The Tanh-sigmoid activation function is used for the hidden layer, while the softmax function is used for the output layer.

## 3. Results and discussion

As we have mentioned earlier, the general objective of this study is to evaluate and predict the solvency of Egyptian insurance companies. So in order to achieve this goal, the empirical analysis has been conducted in three steps. The first step is the financial analysis of the Egyptian property-liability insurance market from 2009/2010 to 2018/2019, involving computing the financial ratios for each company and comparing them with the standard limits. In this way, the authors could arrange the companies according to achieving these standard limits. The second step included determining the most factors that influence the solvency of the Egyptian insurance market using the logistic regression analysis (LR) during the study period. At the same time, the third step involved using the artificial neural network to predict the solvency of the Egyptian insurance market for the year 2020.

### *3.1. The financial analysis results*

Table 2 shows the total results of calculating the 11 financial ratios for all companies included in the study during the period from 2009/2010 to 2018/2019, and the authors could arrange these companies according to their ability to achieve the greatest possible commitment to these financial ratios as is shown in Table 3.

As appears from Table 3, AROPE Insurance Egypt comes first with a score of 99.09% of the total points of achieving financial ratios, followed by Delta Insurance which comes in second place with a score of 93.64%. While Royal Insurance came third with a score of 92.73%, and both Misr Insurance and Mohandes Insurance companies came in fourth place with a score of 91.82%. Arab Misr Insurance Group and Allianz Egypt got a fifth place with the same score of 89.09%. The sixth place was to Iskan Insurance Company with a score of 87.27%, while the seventh place was to AIG Egypt with a score of 75.45% and Suez Canal Insurance Company came eighth with a score of 74.55%. Chubb Insurance and Bupa Egypt Insurance got last place with a score of 71.82% of the total points of achieving financial ratios. It becomes evident now that the property-liability insurance companies in the Egyptian market do not have the same degree of financial solvency, and there is an obvious difference among them in terms of total solvency. To confirm this result and to determine the extent of a difference among these companies, the authors have tested the following hypothesis; there is a statistically significant difference in solvency among companies in the Egyptian insurance market. An analysis of the variance of the 11 financial ratios was applied using the software IBM SPSS Statistics, and the result is shown in Tables 4 and 5.

**Table 2.** The result of the financial analysis for the Egyptian Insurance market from 2010 to 2019.

| Ratio | $X_1$ | | $X_2$ | | $X_3$ | | $X_4$ | | $X_5$ | | $X_6$ | | $X_7$ | | $X_8$ | | $X_9$ | | $X_{10}$ | | $X_{11}$ | | Total | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Company | In | Out | In | Out | In | Out | In | In | In | Out | In | Out | In | Out | In | Out | In | Out | In | Out | In | Out | In | Out |
| Misr Insurance | 10 | 0 | 10 | 0 | 9 | 1 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 4 | 6 | 10 | 0 | 8 | 2 | 10 | 0 | 101 | 9 |
| Suez Canal Insurance (SCI) | 8 | 2 | 6 | 4 | 6 | 4 | 6 | 4 | 10 | 0 | 10 | 0 | 0 | 10 | 6 | 4 | 10 | 0 | 10 | 0 | 10 | 0 | 82 | 28 |
| Mohandes Insurance (MIC) | 10 | 0 | 10 | 0 | 8 | 2 | 10 | 0 | 9 | 1 | 10 | 0 | 7 | 3 | 7 | 3 | 10 | 0 | 10 | 0 | 10 | 0 | 101 | 9 |
| Delta Insurance (DEIN) | 10 | 0 | 10 | 0 | 9 | 1 | 10 | 0 | 10 | 0 | 10 | 0 | 9 | 1 | 5 | 5 | 10 | 0 | 10 | 0 | 10 | 0 | 103 | 7 |
| AIG Egypt | 10 | 0 | 10 | 0 | 3 | 7 | 9 | 1 | 10 | 0 | 10 | 0 | 5 | 5 | 1 | 9 | 8 | 2 | 7 | 3 | 10 | 0 | 83 | 27 |
| Arab Misr Insurance Group (gig) | 10 | 0 | 10 | 0 | 3 | 7 | 10 | 0 | 10 | 0 | 10 | 0 | 7 | 3 | 8 | 2 | 10 | 0 | 10 | 0 | 10 | 0 | 98 | 12 |
| Chubb (ACE) insurance | 10 | 0 | 10 | 0 | 0 | 10 | 10 | 0 | 9 | 1 | 10 | 0 | 9 | 1 | 0 | 10 | 6 | 4 | 5 | 5 | 10 | 0 | 79 | 31 |
| Royal Insurance | 10 | 0 | 8 | 2 | 10 | 0 | 9 | 1 | 10 | 0 | 10 | 0 | 10 | 0 | 8 | 2 | 10 | 0 | 10 | 0 | 7 | 3 | 102 | 8 |
| Allianz Egypt | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 5 | 5 | 8 | 2 | 10 | 0 | 5 | 5 | 10 | 0 | 98 | 12 |
| Bupa Egypt Insurance | 10 | 0 | 10 | 0 | 3 | 7 | 10 | 0 | 10 | 0 | 10 | 0 | 0 | 10 | 0 | 10 | 8 | 2 | 8 | 2 | 10 | 0 | 79 | 31 |
| AROPE INSURANCE EGYPT | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 9 | 1 | 10 | 0 | 10 | 0 | 109 | 1 |
| Iskan Insurance | 10 | 0 | 10 | 0 | 6 | 4 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 8 | 2 | 6 | 4 | 6 | 4 | 10 | 0 | 96 | 14 |

**Table 3.** The Order of the companies in the Egyptian insurance market.

| Position | Company | Percentage of achieving the standard limits |
|---|---|---|
| 1st | AROPE Insurance Egypt | 109/110 = 99.09% |
| 2nd | Delta Insurance (DEIN) | 103/110 = 93.64% |
| 3rd | Royal Insurance | 102/110 = 92.73% |
| 4th | Misr Insurance- Mohandes Insurance (MIC) | 101/110 = 91.82% |
| 5th | Arab Misr Insurance Group (gig) - Allianz Egypt | 98/110 = 89.09% |
| 6th | Iskan Insurance | 96/110 = 87.27% |
| 7th | AIG Egypt | 83/110 = 75.45% |
| 8th | Suez Canal Insurance (SCI) | 82/110 = 74.55% |
| 9th | Chubb (ACE) Insurance- Bupa Egypt Insurance | 79/110 = 71.82% |

**Table 4.** Descriptives of the financial ratio from 2009/2010 to 2018/2019.

| company | N | Mean | Std. Deviation | Std. Error |
|---|---|---|---|---|
| Misr Insurance Company | 110 | 98.5703 | 154.57332 | 14.73799 |
| Suez Canal Insurance | 110 | 96.1414 | 103.01206 | 9.82181 |
| Mohandes Insurance | 110 | 74.0474 | 85.86917 | 8.18730 |
| Delta Insurance | 110 | 69.3694 | 71.08569 | 6.77775 |
| AIG Egypt company | 110 | 76.7578 | 107.65922 | 10.26490 |
| Arab Misr Insurance Group gig | 110 | 76.0481 | 72.92949 | 6.95355 |
| Chubb (ACE) insurance | 110 | 132.9766 | 415.07150 | 39.57551 |
| Royal Insurance company | 110 | 107.9389 | 103.74672 | 9.89186 |
| Allianz Egypt | 110 | 95.6093 | 92.63061 | 8.83198 |
| Bupa Egypt Insurance | 110 | 65.7325 | 70.44429 | 6.71660 |
| AROPE INSURANCE EGYPT | 110 | 67.3964 | 127.89989 | 12.19478 |
| Iskan Insurance | 110 | 70.9612 | 85.01433 | 8.10580 |
| Total | 1320 | 85.9624 | 154.45599 | 4.25126 |

**Table 5.** ANOVA.

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 509,106.073 | 11 | 46,282.370 | 1.955 | 0.029 |
| Within Groups | 30,957,817.892 | 1308 | 23,668.056 | | |
| Total | 31,466,923.964 | 1319 | | | |

Table 5 shows that there is a statistically significant difference in the solvency among companies in the Egyptian insurance market.

### 3.2. *Logistic regression analysis results*

According to Fernandes et al., 2021, identifying the dependent variable, which should be naturally dichotomous, is an essential part of performing the logistic regression, and it counts as the first step of the analysis. Therefore, the authors classified the 12 companies according to the efficiency level of the financial performance per year into two categories: troubled (insolvent) and financially stable (solvent). The company, which has four ratios or more per year, falls outside the usual range will be considered insolvent otherwise, it will be solvent. Based on this criterion the dependent variable is binary and we indicate 1 to solvent companies and 0 to insolvent ones, and the independent variables are the 11 financial ratios that were selected as predictor variables. At our disposal, there are 120 cases included in the analysis divided into 109 solvent cases (Y = 1) and 11 insolvent cases (Y = 0). Table 6 summarizes this distribution.

**Table 6.** The frequency distribution of the response variable.

| Y& encoding | Frequency | % |
|---|---|---|
| solvent 1 | 109 | 90.83 |
| Insolvent 0 | 11 | 9.17 |
| Total | 120 | 100.00 |

As stated above, that one of the interests of this study is to determine the ratios that have the most influence among those 11selected financial ratios on the solvency of companies in the Egyptian insurance market. To achieve this, Forward Stepwise Logistic regression analysis was carried out employing IBM SPSS Statistics software, and the results were generated in Table 7. The result of the third model represented in step 3 in Table 7 showed that ratios x3, x7, and x10 are the most significant independent variables among the 11 variables included in the model with (p-value) = 0.014, 0.029, and 0.023, respectively, and all are statistically significant at the significance level of $\alpha = 0.05$.

**Table 7.** Variables in the Equation (the most significant variables).

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 3 | X3 | 0.246 | 0.100 | 6.071 | 1 | 0.014 | 1.279 |
| | X7 | -0.410- | 0.187 | 4.794 | 1 | 0.029 | 0.663 |
| | X10 | 2.051 | 0.901 | 5.179 | 1 | 0.023 | 7.773 |
| | Constant | -9.259- | 4.201 | 4.858 | 1 | 0.028 | 0.000 |

In terms of the overall model evaluation, the measures which most commonly used to test the logistic regression model's goodness of fit are the −2 log-likelihood, chi-square, Hosmer and Lemeshow test, Cox & Snell's pseudo $R^2$, and Nagelkerke's pseudo $R^2$ (Fernandes et al., 2021). Tables 8 and 9 show these measures.

**Table 8**. Model's goodness of fit measures.

| Step | −2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|---|
| 1 | 43.726 | 0.220 | 0.480 |
| 2 | 23.844 | 0.339 | 0.740 |
| 3 | 12.144 | 0.400 | 0.874 |

As can be seen from Table 8 that the model 3 has an excellent fit to model 1 and model 2 as the −2 Log-likelihood value of model 3 is (12.144), and it is the least value among the three models. In addition, the values of Cox & Snell $R^2$ and Nagelkerke $R^2$ are (0.4) and (0.874) respectively in model 3 while they are (0.339 & 0.74) in model 2 and (0.22 &0.48) in model 1.

**Table 9**. Hosmer and Lemeshow Test.

| Step | Chi-square | df | Sig. |
|---|---|---|---|
| 1 | 2.292 | 8 | 0.971 |
| 2 | 7.745 | 8 | 0.459 |
| 3 | 0.088 | 8 | 1.000 |

Similarly, it is visible from Table 9 that model 3 has an insignificant result ($p = 1 > 0.05$) which means that model 3 has a perfect fit. Unlike the Hosmer and Lemeshow test. In the Omnibus tests of model coefficients, a significant result ($p < 0.05$) suggests a sufficient fit (Garson, 2011). According to Table 10, model 3 has a chi-square of 61.386 (p-value < 0.05), Thus, we should conclude that x3, x7, and x10 influence the dependent variable's variation.

**Table10.** Omnibus Tests of Model Coefficients.

| | | Chi-square | df | Sig. |
|---|---|---|---|---|
| Step 3 | Step | 11.700 | 1 | 0.001 |
| | Block | 61.386 | 3 | 0.000 |
| | Model | 61.386 | 3 | 0.000 |

*3.3. Neural Network results.*

In this stage, the authors used Matlab R2020a to build an artificial neural network model for predicting the solvency of insurance companies in the Egyptian market. Implementation of our neural network involved a number of steps as following.

Step 1: Presenting the inputs and target data to the network.

The inputs data for our network have been the selected 11 financial ratios and the desired output was efficiency level of the financial performance as 1 were given to the companies that were solvent and 0 were assigned to those that were insolvent.

Step 2: Designing the neural network architecture.

Different networks architectures were implemented with different numbers of hidden layers and different numbers of its neurons. In each architecture, we estimated the error and the misclassification cost, and finally, we chose the network with the least error and zero misclassification cost. The optimal design for our network was built using 1 hidden layer with 10 neurons. In addition, our target output is binary 0 or 1; therefore, the output layer just contained 1 neuron. Therefore, our neural network consisted of 1 hidden layer with 10 neurons and 1 output with 1 neuron. For the hidden layer, we had Tanh sigmoid as an activation function, while we applied the Softmax function for the output layer with Cross-entropy loss (see Figure 1).

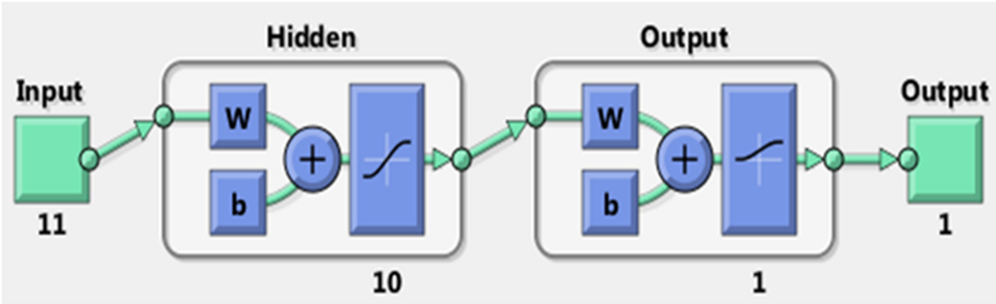


**Figure 1.** The neural network architecture.

Step 3: Data dividing.

The data sample was randomly divided into 3 subsamples: training, validation, and test samples, respectively (Vanstone & Finnie 2009); Table 11summarizes this dividing.

**Table 11**. The subsamples in our model.

| Samples | % | N |
|---|---|---|
| Training | 70% | 84 |
| Validation | 15% | 18 |
| Test | 15% | 18 |
| Total | 100% | 120 |

Step 4: Training the network.

Our ANN was trained using scaled conjugate gradient backpropagation and the results are shown below.

From Table 12, we can see that the designed model could identify the given pattern of training samples with 100% correct percentage and misclassification cost equal to zero and the same result for the validation and tests samples. This means that the ANN model could classify the test samples to the prior target variable (see Figure 2).

**Table 12**. Performance of the neural network model.

| | classification accuracy | | |
|---|---|---|---|
| Samples | correctly classified | Percentage of corrects (%) | misclassification cost |
| Training | 74/74 | 100% | 0 |
| Validation | 17/17 | 100% | 0 |
| Test | 18/18 | 100% | 0 |
| overall | 109/109 | 100% | |

The ROC curves appear in Figure 3 suggests that our ANN model is working well as the area under the curve equals 1, which also means that the model is a perfect classifier. By looking at Figure 4, which shows the Cross-entropy loss value ($5.3588e^{-05}$), we conclude that the performance of a classification model is excellent, i.e., the predicted outputs do not diverge from the actual data outputs.


**Figure 2.** Confusion (classification) matrix.

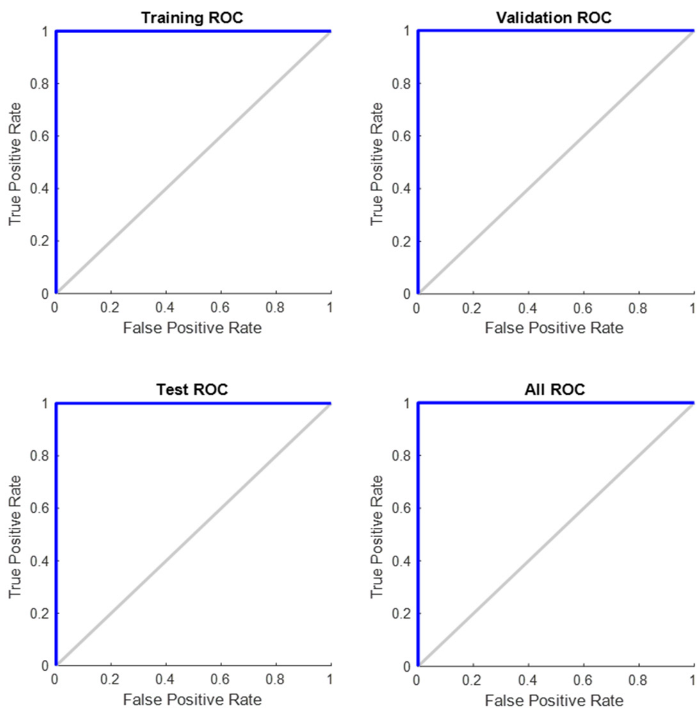


**Figure 3**. Receiver operating characteristic (ROC) curves.

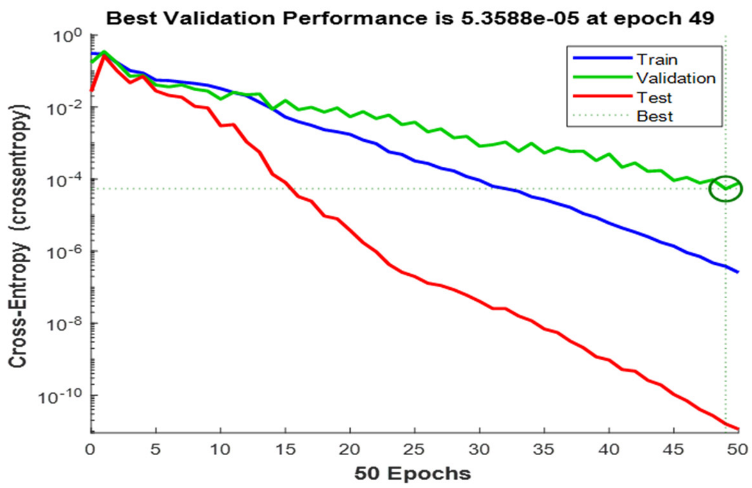


**Figure 4.** Cross-entropy loss.

3.3.1. Prediction those companies' solvency for the year 2019/2020

Here, we used our trained network to predict solvency of the Egyptian insurance companies for the next year 2020. We had saved our network to Matlab's workspace in order to use it with new data representing the financial ratios (x1, x2, x3 … X11) related to the year, 2020 which had been calculated for all companies, and we got the result shown in Table 13.

**Table 13.** The result of the trained neural network.

| Company | Predicted outputs | Actual outputs |
|---|---|---|
| Misr Insurance Company | 1.0000 | 1 |
| Suez Canal Insurance | 0.9999 | 1 |
| Mohandes Insurance | 1.0000 | 1 |
| Delta Insurance | 1.0000 | 1 |
| AIG Egypt company | 1.0000 | 1 |
| Arab Misr Insurance Group gig | 1.0000 | 1 |
| Chubb (ACE) insurance | 0.0000 | 1 |
| Royal Insurance company | 1.0000 | 1 |
| Allianz Egypt | 1.0000 | 1 |
| Bupa Egypt Insurance | 0.0000 | 0 |
| AROPE INSURANCE EGYPT | 1.0000 | 1 |
| Iskan Insurance | 1.0000 | 1 |

As it is shown from Table 13 that the trained ANN was able to classify 11 cases of 12 cases correctly, i.e., the prediction accuracy of our model for future solvency is 91.67%. Lastly, we conclude that we can use the trained artificial neural network as a new early warning model to identify companies in the Egyptian market suffering from financial distress.

## 4. Conclusions

This paper utilizes eleven financial ratios to examine the financial performance efficiency level of all property and liability insurance companies in Egypt during the period from 2009/2010 to 2018/2019. This study aims to analyze these companies and the financial analysis results for those companies outputted that AROPE Insurance Egypt company, Delta Insurance company, Royal Insurance company and both Misr Insurance and Mohandes Insurance companies are most companies which have excellent financial performance with performance efficiency level scores 99.09%, 93.64%, 92.73%, and 91.82% respectively. In contrast, both Arab Misr Insurance Group, Allianz Egypt Companies, and Iskan Insurance Company have a good financial performance with scores of 89.09% and 87.27%, respectively. Moreover, AIG Egypt, Suez Canal Insurance, and Chubb Insurance Company, with scores of 75.45% and 74.55%, have quite poor financial performance efficiency compared to the previous companies. However, the point to be noted is that Bupa Egypt Insurance achieves the least level of financial performance with a score of 71.82%. We conclude that the property and liability insurance companies in the Egyptian market do not have the same degree of solvency.

This paper investigates using of the Logistic Regression model in determining the most significant ratios among those eleven financial ratios that influence the performance of companies in the Egyptian insurance market. The results of the LR showed that "Risk retention rate", "Insurance account receivable to total assets", and "Net profit after tax to total assets" are the most factors that affect the financial performance for those companies.

Furthermore, this study proposes a multi-layer artificial neural network with a backpropagation algorithm as an efficient and reliable predictive tool in classifying the Egyptian insurance companies into two groups of solvent and insolvent categories. The proposed ANN model managed to correctly re-classify these companies where its accuracy in discriminating between the solvent and insolvent companies was 100%. Lastly, the financial ratios were used to predict these companies' solvency in 2020 using the trained ANN model. The result of the prediction shows that ANN is an efficient prediction model with a powerful predictive accuracy in a way that let the Egyptian regulators look at this new intelligence model as an alternative model for the current models employed in the Egypt insurance market, and they can depend on it for examining the financial performance of insurance companies.

## Acknowledgments

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

## Conflict of interest

All authors declare no conflicts of interest in this paper.

## References

Affes Z, Hentati-Kaffel R (2019) Predicting US banks bankruptcy: logit versus Canonical Discriminant analysis. *Comput Econ* 54: 199–244.

Altman EI, Haldeman R, Narayanan P (1977) ZETA Analysis, a New Model for Bankruptcy Classification. *J Bank Financ* 1: 29–54.

Altman EI (1968) Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *J Financ* 23: 589–609.

Altman EI, Iwanicz-Drozdowska M, Laitinen EK, et al. (2020) A race for long horizon bankruptcy prediction. *Appl Econ* 52: 4092–4111.

Atiya AF (2001) Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results. *IEEE Tran Neural Networks* 12: 929–935.

Back B, Laitinen T, Sere K, et al. (1996) Choosing Bankruptcy Predictors Using Discriminant Analysis, Logit Analysis, and Genetic Algorithms. Technical Report No. 40. Turku Centre for Computer Science, Turku.

Baranoff EG, Sager TW, Shively TS (2000) A Semiparametric Stochastic Spline Model as a Managerial Tool for Potential Insolvency. *J Risk Insur* 67: 369–396.

BarNiv R, McDonald JB (1992) Identifying Financial Distress in the Insurance Industry: A Synthesis of Methodological and Empirical Issues. *J Risk Insur* 59: 543–573.

BarNiv R, Hershbarger RA (1990) Classifying Financial Distress in the Life Insurance Industry. *J Risk Insur* 57: 110–136.

Beaver WH (1966) Financial ratios as predictors of failure. *J Account Res* 4: 71–111.

Berthold M, Hand DJ (2003) *Intelligent data analysis*. Vol. 2. Berlin: Springer.

Bradley AP (1997) The use of the area under the ROC curve in the evaluation of machine learning algorithms. *Pattern Recognit* 30: 1145–1159.

Brockett LP, Cooper WW, Golden LL, et al. (1994) A neural network method for obtaining an early warning of insurer insolvency. *J Risk Insur* 61: 402–424.

Brockett LP, Golden LL, Jang J, et al. (2006) A comparison of neural network, statistical methods, and variable choice for life insurers. *J Risk Insur* 73: 397–419.

Burca AM, Batrinca G (2014) The Determinants of Financial Performance in the Romanian Insurance Market. *Int J Acad Res Accounti Financ Manage Sci* 4: 299–308.

Carson JM, Hoyt RE (1995) Life Insurer Financial Distress: Classification Models and Empirical Evidence. *J Risk Insur* 62: 764–775.

Carson JM, Hoyt R (2000) Evaluating the Risk of Life Insurer Insolvency: Implications From the US for the European Union. *J Multinatl Financ Manage* 10: 297–314.

Cheng J, Weiss MA (2012) The Role of RBC, Hurricane Exposure, Bond Portfolio Duration, and Macroeconomic and Industry-wide Factors in Property—Liability Insolvency Prediction. *J Risk Insur* 79: 723–750.

Chen R, Wong KA (2004) The Determinants of Financial Health of Asian Insurance Companies. *J Risk Insur* 71: 469–499

Choi RY, Coyner AS, Kalpathy-Cramer J, et al. (2020) Introduction to machine learning, neural networks, and deep learning. *Transl Vision Sci Technol* 9: 14.

Cummins JD, Grace MF, Phillips RD (1999) Regulatory Solvency Prediction in Property Liability Insurance: Risk-Based Capital, Audit Ratios, and Cash Flow Simulation. *J Risk Insur* 66: 417–458.

Fernandes AAT, Figueiredo DB, Rocha EC, et al. (2021) Read this paper if you want to learn logistic regression. *Rev Sociol Polit* 28: e006.

Garson GD (2011) Multiple regression: Overview. *Statnotes: Topics in Multivariate Analysis*.

Garson GD (2014) *Logistic regression: Binary and multinomial*. Asheboro, NC.

Gross EP, Vozikis GS (2000) Prediction of Insolvency of Life Insurance through Neural Networks. In *ECIS 2000 Proceedings*.

Gschwind M (2007) Predicting late payments: A study in tenant behavior using data mining techniques. *J Real Estate Portf Manage* 13: 269–288.

Hair JF, Black WC, Babin BJ, et al. (2009) *Análise multivariada de dados*. Bookman editora.

Hara K, Kataoka H, Satoh Y (2017) Learning spatio-temporal features with 3d residual networks for action recognition. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, 3154–3160.

Hosmer DW, Lemeshow S (2000) *Applied Logistic Regression*. New York: John Wiley & Sons.

Hsiao SH, Whang TJ (2009) A Study of Financial Insolvency Prediction Model for Life Insurers. *Expert Syst Appl* 36: 6100–6107.

Huang CS, Dorsey RE, Boose MA (1994) Life Insurer Financial Distress Prediction: A Neural Network Model. *J Insur Regul* 13: 131–167.

Kennedy P (2008) *A guide to econometrics*. John Wiley & Sons.

Kohonen T, Hynninen J, Kangas J, et al. (1996) LVQ PAK: The LearningVector Quantization Program Package. Helsinki University of Technology, Technical report.

Kristóf T (2004) Mesterséges intelligencia a csõdelõrejelzésben [Artificial Intelligence in BankruptcyPrediction]. Jövõtanulmányok 21. Budapest: Future Theories Centre, BUESPA.

Krogh A (2008) What are artificial neural networks? *Nat Biotechnol* 26: 195–197.

Lee SH, Urrutia JL (1996) Analysis and Prediction of Insolvency in the Property-Liability Insurance Industry: A Comparison of Logit and Hazard Models. *J Risk Insur* 63: 121–130.

Maas AL, Hannun AY, Ng AY (2013) Rectifier nonlinearities improve neural network acoustic models. In *Proc. Icml*, 30: 3.

Menard S (2002) *Applied logistic regression analysis*. Sage.

Mollahosseini A, Chan D, Mahoor MH (2016) Going deeper in facial expression recognition using deep neural networks. In *2016 IEEE Winter conference on applications of computer vision (WACV)*, IEEE, 1–10.

Negnevitsky M (2011) *Artificial intelligence: a guide to intelligent systems*. Third Edition.

Ohlson JA (1980) Financial ratios and the probabilistic prediction of bankruptcy. *J Account Res* 18: 109–131.

Ooghe H, Claus H, Sierens N, et al. (1999) *International Comparison of Failure Prediction Models from Different Countries: An Empirical Analysis*. Department of Corporate Finance, University of Ghent.

Park HA (2013) An introduction to logistic regression: from basic concepts to interpretation with particular attention to nursing domain. *J Korean Acad Nurs* 43: 154–164.

Pinches GE, Trieschmann JS (1974) The Efficiency of Alternative Models for Solvency Surveillance in the Insurance Industry. *J Risk Insur* 41: 563–577.

Ping W, Peng K, Gibiansky A, et al. (2017) Deep voice 3: Scaling text-to-speech with convolutional sequence learning. arXiv preprint, arXiv:1710.07654.

Pottier SW, Sommer DW (2002) The Effectiveness of Public and Private Sector Summary Risk Measures in Predicting Insurer Insolvencies. *J Financ Serv Res* 21: 101–116.

Sharpe IG, Stadnik A (2007) Financial Distress in Australian General Insurers. *J Risk Insur* 74: 377–399.

Stephenson B, Cook D, Dixon P, et al. (2008) Binary response and logistic regression analysis. Available from: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.142.6636&rep=rep1&type=pdf.

Szandała T (2021) Review and Comparison of Commonly Used Activation Functions for Deep Neural Networks. In: Bhoi AK, Mallick PK, Liu CM, et al., *Bio-inspired Neurocomputing*. Springer, Singapor, 203–224.

Trieschmann JS, Pinches GE (1973) A Multivariate Model for Predicting Financially Distressed P-L Insurers. *J Risk Insur* 40: 327–338.

Vanstone B, Finnie G (2009) An empirical methodology for developing stockmarket trading systems using artificial neural networks. *Expert Syst Appl* 36: 6668–6680.

Virág M, Kristóf T (2005) Neural networks in bankruptcy prediction-A comparative study on the basis of the first Hungarian bankruptcy model. *Acta Oecon* 55: 403–426.

Walker J (1996) Methodology Application: Logistic Regression the Using CODES Data. No. HS-808 460. Available from: https://rosap.ntl.bts.gov/view/dot/4427.

Were K, Bui DT, Dick ØB, et al. (2015) A comparative assessment of support vector regression, artificial neural networks, and random forests for predicting and mapping soil organic carbon stocks across an Afromontane landscape. *Ecol Indic* 52: 394–403.

Zekić-Sušac M, Šarlija N, Has A, et al. (2016) Predicting company growth using logistic regression and neural networks. *Croat Oper Res Rev* 7: 229–248.

Zhang L, Nielson N (2015) Solvency Analysis and Prediction in Property–Casualty Insurance: Incorporating Economic and Market Predictors. *J Risk Insur* 82: 97–124.