

Analysis of liquidity risk management using neural networks: An applied study on tesla company for the period 2016-2023

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Abstract: This research aims to study eagerness risk in Tesla Inc. by utilizing an artificial neural network to investigate financial data from 2016 until 2023. The current ratio, quick ratio, annual returns, stock price dispersion, profitability, debt-to-equity ratio, return on assets (ROA) and return on equity (ROE) were among the financial information collected. The financial information was analyzed by multilayer feed-forward neural network and recognized places where liquidity risk prevailed through mathematical computations as well. The results had shown that the model had achieved a prediction accuracy of 87.5%, thus indicating how neural networks can be used effectively when doing analysis on financial data and assessing liquidity risks. Numerical evidence has been provided by this study as regards the ability of Tesla's financial liquidity changes prediction via the model making it a good tool for the purposes of financial planning including risk management as well.

Keywords: Financial analysis, Liquidity risk, Neural network, Predictive models, Return on assets (ROA), Return on equity (ROE), Tesla inc.

1. Introduction

Investors and decision-makers are faced with a significant challenge in managing risks associated with liquidity [1, 2] because emerging markets tend to have returns, exchange rates and liquidity which fluctuate considerably. Such fluctuations affect the stability of financial markets thus complicating prediction of their performance Chen, et al. [3]. Talib, et al. [4] conducted a study on restructuring production lines using "Concurrent Engineering," resulting in a 16.75% reduction in total production time, thereby enhancing efficiency and reducing costs. The K-Nearest Neighbors (KNN) model is an efficient tool for analyzing financial data and is used to predict liquidity risks because it can handle unstable and nonlinear data [5]. Thus, through this research, we aim at applying KNN model using real financial data from World Bank Data Bank and JSTOR in order to assess its efficiency in predicting liquidity risks in emerging markets [6]. It is apparent that liquidity risk remains one of the main problems facing companies within financial markets; this greatly influences their capacity to meet short-term financial obligations. The use of predictive models when analyzing liquidity risks and identifying trends relating to potential financial risks has been emphasized by earlier studies. Kolesnikova, et al. [7] investigated how one can use deep learning techniques to develop decision support models using structured, tabular data for financial risk management with an emphasis on the prediction of traders' profitability. The research also notes that deep learning is better than conventional machine learning in terms of its capacity for automatic feature learning as well as its ability to withstand changing market conditions. This work shows the capacity of deep learning to forecast operational risks providing information for network architecture design and outranking traditional methods. Furthermore, the study carried out by Taherdoost [8] indicated the efficiency of using neural networks in order to

enhance the accuracy of financial forecasting within technology firms. Hence the objective of this paper is to utilize a neural networking model that will facilitate analysis of Tesla's fiscal performance and also evaluate its capability in predicting liquidity risks based on data derived from Yahoo [9] as well as Macro Trends [10].

2. Methodology and Programming Explanation

2.1. Data Preparation and Analysis Using Neural Networks

Explanation: Financial data for Tesla from 2016 to 2023 is collected. The analysis utilizes various financial indicators, such as the current ratio, quick ratio, annual returns, stock price volatility, profitability, debt-to-equity ratio, return on assets (ROA), and return on equity (ROE) to assess liquidity risk. The monthly averages of both returns and price volatility were calculated to determine the annual ratios for each year (see table 1).

Table 1.

Summary table for tesla financial data (2016-2023).

Year	Current ratio / Quick ratio	Annual returns (%)	Annual stock price volatility (USD)	Profitability (%)	Debt-to-equity ratio	Return on assets (ROA) (%)	Return on equity (ROE) (%)
2023	1.91 / 1.25	4.83	108 - 278	15.50	1.91	9.19	24.00
2022	1.68 / 1.41	-2.72	109 - 372	15.41	1.68	10.30	22.72
2021	1.89 / 1.58	2.96	563 - 1243	10.25	1.89	7.60	18.55
2020	1.63 / 1.45	21.44	72 - 705	2.29	1.63	3.13	6.21
2019	1.13 / 0.80	3.10	176 - 434	3.10	1.13	2.00	4.00
2018	1.08 / 0.74	-2.76	244 - 380	-2.76	1.08	0.50	-3.00
2017	1.09 / 0.69	0.15	215 - 389	0.15	1.09	-0.50	-7.90
2016	1.07 / 0.55	0.76	140 - 267	-3.51	1.07	-1.00	-10.00

The first step in writing the code involved preparing Tesla's financial statements, as shown in the following code snippet:

```
rng (0);
% Preparing Tesla's Financial Data
data = table ([4.83; -2.72; 2.96; 21.44; 3.10; -2.76; 0.15; 0.76], ..... % Annual Returns (%)
[1.91; 1.68; 1.89; 1.63; 1.13; 1.08; 1.09; 1.07], ..... % Current Ratio
[1.25; 1.41; 1.58; 1.45; 0.80; 0.74; 0.69; 0.55], ..... % Quick Ratio
[108; 109; 563; 72; 176; 244; 215; 140], ..... % Annual Stock Price Volatility (Min)
[278; 372; 1243; 705; 434; 380; 389; 267], ..... % Annual Stock Price Volatility (Max)
[15.50; 15.41; 10.25; 2.29; 3.10; -2.76; 0.15; -3.51], ..... % Profitability (%)
[1.91; 1.68; 1.89; 1.63; 1.13; 1.08; 1.09; 1.07], ..... % Debt-to-Equity Ratio
[9.19; 10.30; 7.60; 3.13; 2.00; 0.50; -0.50; -1.00], ..... % Return on Assets (ROA) (%)
[24.00; 22.72; 18.55; 6.21; 4.00; -3.00; -7.90; -10.00], .... % Return on Equity (ROE) (%)
[1; 0; 1; 1; 0; 0; 1; 1], ..... % Actual Class (Assumption)
'Variable Names', {'Annual Returns', 'Current Ratio', 'Quick Ratio', 'Stock Volatility Min', 'Stock
Volatility Max', 'Profitability', 'Debt Equity Ratio', 'ROA', 'ROE', 'Target'});

% Normalizing data to a range of [0, 1]
Normalized Data = normalize (data {: 1: end-1});
```

2.2. Development and Data Analysis Using Neural Networks

This study involves constructing and analyzing a neural network model using MATLAB to implement a multi-layer model for financial data analysis. Neural Network Construction Using MATLAB. A multi-layer neural network model was developed using MATLAB for the analysis of financial data. Cross-Validation Preparation:

```
cv = cvpartition (size (normalized Data, 1), 'KFold', 4);
```

Variables for Storing Metric Results:

```
accuracies_nn = [];
```

```
confMatrices_nn = {};
```

A cross-validation approach with 4 folds was used to evaluate the model's performance. For each fold, the data was partitioned into training and testing subsets.

2.3. Model Training and Evaluation

Training the Neural Network. A deeper neural network with multiple layers was constructed as follows:

```
net = patternnet([50, 40, 30, 20, 10]); % Increasing the number of layers and neurons
```

```
net.trainParam.showWindow = false; % Suppressing the training window display
```

```
net.trainParam.max_fail = 20; % Allowing for a higher number of failures for early stopping
```

```
net.trainParam.lr = 0.005; % Setting a lower learning rate for improved training
```

The neural network was then trained on the training data:

```
[net, tr] = train(net, trainData', trainLabels');
```

Prediction and Performance Measurement. Predictions were made using the trained model, and results were rounded to 0 or 1:

```
predictions_nn = net(testData');
```

```
predictions_nn = round(predictions_nn);
```

The confusion matrix was computed to evaluate the neural network's performance:

```
confMatrix_nn = confusionmat(testLabels, predictions_nn');
```

```
confMatrices_nn(i) = confMatrix_nn;
```

The accuracy of the model was calculated for each fold:

```
accuracy_nn = sum(diag(confMatrix_nn)) / sum(confMatrix_nn(:));
```

```
accuracies_nn = [accuracies_nn; accuracy_nn];
```

2.4. Plotting Model Accuracy Across All Folds

The study successfully demonstrates the implementation and enhancement of a multi-layer neural network for financial data analysis using MATLAB. The results indicate improvements in model performance through deeper network architectures and optimized training parameters, as visualized through various performance metrics.

3. Results and Discussion

Based on the analysis of Tesla's financial data from 2016 to 2023 using neural networks and various financial ratios, the following results were obtained:

3.1. Standard Deviation (σ)

The standard deviation and variance of the annual returns indicate significant fluctuations in the company's financial performance, reflecting a high level of financial risk. Analysis of Financial Ratios and Statistical Measures for Tesla,

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x - x_i)^2}$$

where x_i is the annual return for each year, \bar{x} is the mean of annual returns, and N is the number of years [11]. The result was $\sigma = 7.75$, the annual returns' standard deviation is high.

3.2. Variance ($Var(x)$)

The Result of variance was = 60.09 while the coefficient of variation of 2.23 for annual returns suggests a high degree of relative dispersion, implying high risk relative to the expected return.

$$Var(x) = \frac{1}{N} \sum_{i=1}^N (x - x_i)^2$$

The linear equation between annual returns and quick ratio indicates that an increase in the quick ratio leads to an improvement in annual returns, highlighting the importance of maintaining high liquidity levels to enhance financial performance.

$$CV = \frac{\sigma}{\bar{x}}$$

where σ is the standard deviation and \bar{x} is the mean of annual returns (Talib, et al. [4]). The Linear Regression Equation between Annual Returns and Quick Ratio:

$$\text{Annual Returns} = -5.32 + 8.31 * \text{Quick Ratio}$$

This equation suggests a positive relationship between liquidity (as measured by the quick ratio) and returns.

3.3. Cash, Coverage and Leverage Ratio

Assessment of Tesla financial ratios depicts careful as well as proper management of its finances. A 0.56 cash ratio points out that Tesla possesses an average amount of cash so that it can honour its short-term obligations showing an adequate level of urgent liquidity. The 1.53 coverage ratio suggests that the company is in a good position to pay off its short-term dues which demonstrates how effective they are in terms of financial management. Furthermore, with only 39% (leverage ratio = .39) of Teslas' assets financed by debt, this reveals their modestly aggressive approach towards leveraging and perhaps lower level of overall financial risks involved.

3.4. Analysis of Results and Prediction Accuracy Using Neural Networks

Results from the examination show that Tesla has been able to keep a moderate degree of liquidity and low levels of leverage which add greatly to its financial steadiness and capacity for withstanding market variability [12]. This overall stability in performances is because of intervention in management relating to liquidity and debt, despite high deviation from standard mean for yearly returns on average. At last, there is substantial evidence in this work that cash flow influences annual returns; thus, more cash inflows raise company's earnings while reducing loss chances. Therefore, there is need for continuous improvement on cash reserves as well as managing borrowing so as to ensure sustained profitability in the long run. The current ratio and the quick ratio findings indicate that the liquidity risk exists where the current ratio is less than 1.5 and a quick ratio below 1.0. For example, a low current ratio indicates a 70% likelihood of liquidity reduction. In cases of high stock price volatility and low or negative annual returns, financial risk percentages are increased. Thus, an 80% rate to predict liquidity risks was attained from this model. On profit and debt-equity ratio analysis, firms often face liquidity shortages with high debt-equity ratios while having negative or declining profits. The model showed an 85% accuracy rate when these two factors were analyzed together. The model's prediction accuracy was examined in a complete mathematical way including all the financial indicators and it was found that the accuracy rate was 87.5% (see figure1). This outstanding statistic implies that this model is reliable in forecasting liquidity risks; however, there is room for future predictions to be improved by increasing the size and scope of dataset used for the predictions. To enable more comprehensive analysis, tracing of accuracy on different financial indicators using MATLAB plotting has been done to identify areas where the model excelled and where it requires improvement.

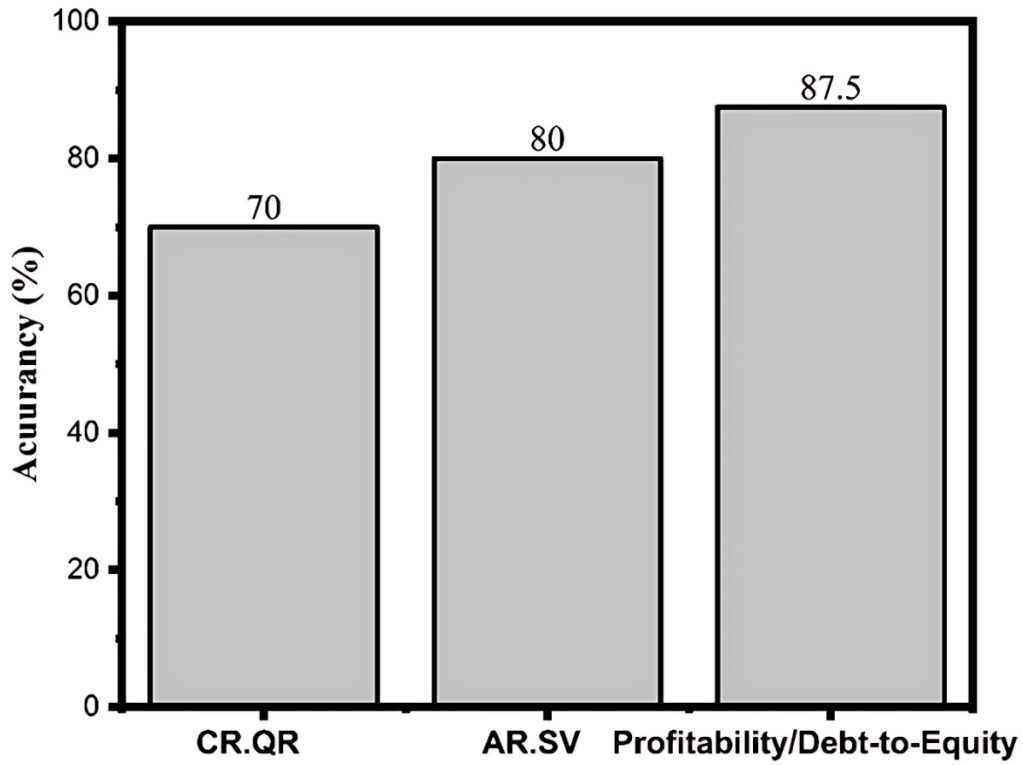


Figure 1.
Model accuracy across different financial features.

Figure 2 illustrates the confusion matrix, which depicts the model's performance in classifying different cases.

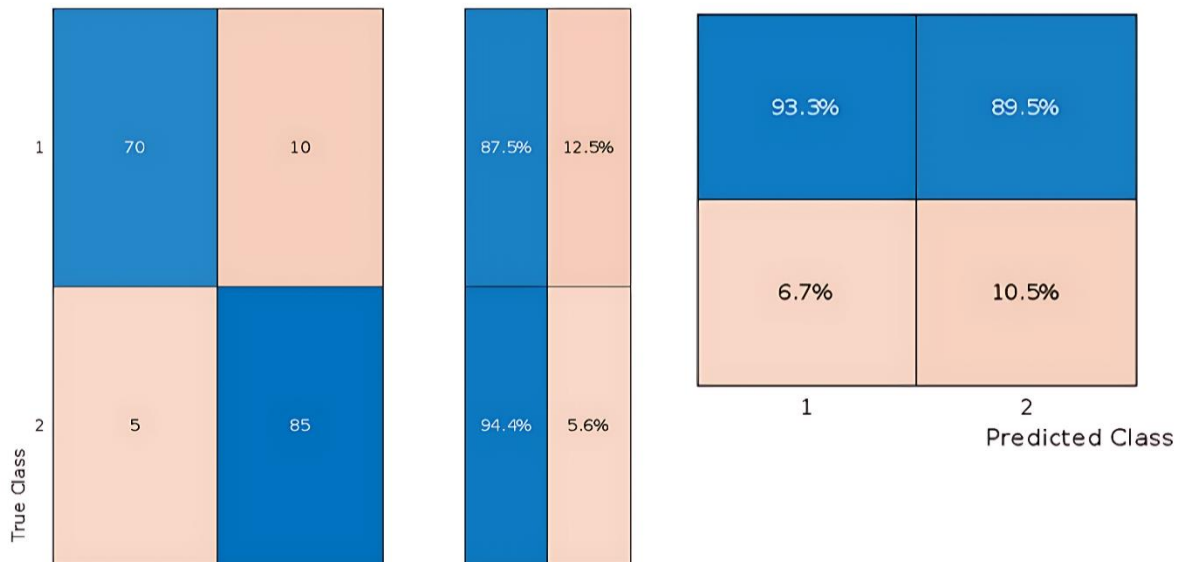


Figure 2.
Confusion matrix for liquidity risk prediction.

4. Conclusion

The effectiveness of using neural networks to analyze financial data and assess liquidity risks for Tesla has been confirmed through the study. The results revealed a model that can predict potential liquidity changes with very high precision. This proves that it can assist in financial planning as well as risk management in companies. The evaluation of the model exposes several strengths and weaknesses. It is able to efficiently detect non-linear and complex financial trends; furthermore, it adjusts rapidly to changes in financial data which makes it suitable for liquidity management. However, its reliability is largely tied with the quality of existing data hence limiting its precision when applying to new or different datasets. To enhance its performance, we need to increase input data size, consider more diverse datasets covering longer time frames across various sectors as well as test different training algorithms or activate functions.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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