ALTMAN AND OHLSON MODEL IN PREDICTING DISTRESS OF INDIAN COMPANIES: A COMPARISON OF MODELS

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Abstract - Inability to discharge a contractual obligation or inability to fulfil obligations to creditors make a corporation or company insolvent. Different financial ratios are used as independent variables in bankruptcy prediction models, which are built using various statistical methods. For the prediction of default companies, we have used Altman model and Ohlson which gives us a brief figure and result that this method can be used for prediction of failure firms and according to analysis the study shows that the Ohlson's model shows the strongest overall results.

Keywords: Altman, Ohlson, Model, Financial, Companies

INTRODUCTION

One of the most challenging topics in the financial sector is forecasting failure, especially in recent years. It is the ability to foresee whether or not a corporation will go bankrupt. In many cases, it is an important key point for decision-making, particularly in the areas of investment and lending. Setting up an early warning system for company failures based on their financial activity enhances decision-making dramatically **Azayite and Achchab (2019); Cultrera and Brédart(2016)**.. To forecast and estimate the rate of bankruptcy over time on financial ratios, decision-makers use a range of techniques, hypothetical models, statistical techniques, and soft computing techniques. **(Devi and Radhika (2019)); Begović et al (2020); Joshi(2019); Ouenniche et al (2019).** Many techniques are implemented and developed by different authors. Previous study by **Adamko and Chutka (2020); Ouenniche et al (2019); Musah and Agyirakwah (2019)** examined in an economic environment in which companies are continually developing and changing as a result of a variety of factors Businesses now have access to a vast market that covers almost the entirety of Europe, providing them with various business opportunities as well as rivals. Prior research by **Agyirakwah and Musah (2019); Bouwmeester (2020); Prusak(2019); Tian and Hartling (2019)** examined there is a connection between corporate governance characteristics and corporate failure. Nearly every key economy in the world has its fair share of corporate failures of which Ghana is not an exception. In context to develops as well as developing economies. Initial analysis by **Bouwmeester (2020);Affes and Kaffel (2016); Kubickova and Nulicek (2019) ; Song and Peng (2019)** examined corporate bankruptcy prediction is of great notice to numerous stakeholders. Predicting the possibility of bankruptcy can benefit investors assess and select firms to invest in, to prevent the risk of losing their investment and an early warning system to prevent bankruptcy. Prior research by **Hosaka (2019); Khan and Raj (2019);Aalbers (2019); Khaerunnisa and Rahayu (2019)** examined Convolutional neural networks are actuality useful to identification glitches in different fields, and in some parts are showing higher discrimination precisions than conventional methods. Previous survey by **Mai et**

al (2019) examined public firms and show that deep learning models provide a greater prediction performance in finding bankruptcy using textual disclosures.

LITERATURE REVIEW

Prusak (2019) ; Csikosova et al (2019); Mihalovic(2016) ;Gnip and Drotár (2019)   analysed the scientific advances of corporate bankruptcy prediction in order to present and analyse.**Khan and Raj (2019)); (Horak et al (2020))** looked at evaluating the Indian telecom industry's financial health and forecasting the collapse of a few firms. In the Indian Telecom Industry, there are about ten telecom firms, and the top six companies were selected for the market capitalization report.By collecting data from an area bankruptcy prediction model**, Gachi et al(2020); (Ogachi et al(2020)); Khaerunnisa and Rahayu (2019) ; Csikosova et al (2019)**   investigated and attempted to incorporate deep learning models for corporate bankruptcy forecasting using textual disclosures. They had a habit of measuring bankruptcy ratings for the first and second years before bankruptcy. The results show that the most important ratios for the prediction of bankruptcy were inventory turnover, asset turnover, debt-equity ratio, debtor turnover, total asset, debt ratio, current ratio, and dealing capital ratio.Bankruptcy prediction models were studied by **Karas and Režňáková (2020); (Karas and Režňáková (2020));** based on the linear discriminant analysis process. The LDA process, the analysed model, is used in the samples used in companies and the manufacturing industry under investigation. The results of this study revealed that there is a criterion that can be used to extract a grey zone that maximises model accuracy while reducing the number of unevaluated businesses. **Atenii and Asghari. (2020);)); (Bateni and Asghari. (2020))** analyzed main subjects for business and financial institutions in recent decades the bankruptcy predicted by using both logic and genetic algorithm (GA) prediction techniques under sanctioned circumstances. The results suggest that the two models have the capability of predicting bankruptcy and the GA model is more accurate than the logit model in this regard. **Shome and Verma (2020) ;Hosaka (2019) ; Song and Peng (2019); Begović et al (2020); Joshi(2019) ;Devi and Radhika (2019)** generate as many financial ratios as possible from the financial statements of each company in each fiscal year and express the set of ratios as a single grayscale image. To achieve this, each financial ratio is made to correspond to a specific pixel position (x, y-coordinates) and the brightness value of that pixel is set based on the value of the corresponding financial ratio. enterprises delisted due to business failures in one of the Japanese stock markets (Tokyo Stock Exchange, Osaka Securities Exchange, former Nasdaq Japan Standard, former Hercules Standard, former Hercules Growth, or the former Jasdaq) between January 2002 and June 2016 are considered to be bankrupt companies. The reasons for delisting, which can be viewed as de facto bankruptcy are bankruptcy/rehabilitation/reorganization procedures, excessive debt, suspension of bank transactions, and termination of business activities (excluding mergers). proposed a method for applying a CNN to bankruptcy prediction. In our method, a set of financial ratios are represented as a grayscale image where each financial ratio corresponds to a fixed pixel position, and the generated images are used as training data for a CNN based on GoogLeNet. A numerical evaluation revealed that allocating neighboring pixel positions to highly correlated financial ratios is more appropriate for our purpose than placing them at random. **Mai et al (2019) Wang et al(2017) ;Kovacova and Kliestik(2017) ; Alaka et al (2018) ;Le et al(2018) ;Altman et al (2014)** introduced deep learning models for corporate bankruptcy predicting using textual disclosures. Although textual data are common, it is rarely measured in the financial decision support models.Deep knowledge uses layers of neural networks to cutting features from textual data for prediction. construct bankruptcy database by merging three data sources: accounting data from Compustat North America, equity trading data from Center for Research in Security Prices (CRSP), and textual disclosure data from10-K annual filings to the Securities Exchange Commission (SEC). proposed a method Predictive models based on textual data pose challenges to the modeling process for several reasons. First, textual data are natural languages; they cannot be directly used as inputs in many mathematical models. Then use natural language processing (NLP) to transform the textual data into numerical units that a mathematical model can understand. Second, typical textual databases are much greater in size compared to numerical datasets.**H. Son et al (2019); Cultrera and Brédart (2016) ;Horak et al (2020);Shome and Verma (2020) ;Islam et al (2019)** introduced a novel bankruptcy prediction model that uses the financial statement data. The model is based on the machine learning such

as Gradient Boosting Machine (Friedman, 2001) method and data preprocessing. This study applied a method to maintain the maximum number of input variables; this strategy contrasts with previous studies in which input variables were pre-selected. **Chen et al (2019); Giannopoulos and Sigbjornsen (2019) ;Elviani(2020) ; García et al(2015) ;Nanda and Pendharkar (2001)** propose to address bankruptcy prediction problem from the perspective of learning with label proportions, where the unlabeled training data are provided in different bags and only giving the bag-level proportion of instances belonging to a particular class. Then, then contribute two novel prediction methods, termedas Bagged-pSVM and Boosted-pSVM, based on proportion support vector machines and ensemble strategies including bagging and boosting. sufficient experiments are conducted to assess the performance of their proposed ensemble methods, and the experimental results demonstrate their superiority and efficiency on solving the problem of bankruptcy prediction. it solve the problem of bankruptcy prediction from the perspective of learning with label proportions, and then contribute two novel prediction methods, called Bagged-pSVM and Boosted-pSVM, based on proportion support vector machine and ensemble learning strategies including bagging and boosting under a large-margin framework.

RESEARCH METHODOLOGY

In this research financial and market data of various financial distress companies will be taken from the annual reports from NSE and BSE. The companies that are taken from the period 2015-2020 there are many companies that are financial distress of Indian firms.

3.3 STATISTICAL TOOLS

In this research we are going to use descriptive Statistics for comparison of various models.

Models used in the study:

"Altman Z-Score model is a numerical measurement that is used to predict the chances of a business going bankrupt in the next two years Also , Altman (1968) employs multiple discriminant analysis (MDA) to distinguish between bankrupt and non-bankrupt firms based on a set of predesignated financial variables. Altman's Z-score model is considered an effective method of predicting the state of financial distress of any organization by using multiple balance sheet values and corporate income."

Altman Equation :

$Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5$

Z = Overall index, where companies with a cutoff score3

above 2.67 are classified as non-bankrupt. The five ratios Altman uses are:

X1 = Working capital/Total assets

X2 = Retained earnings/Total assets

X3 = Earnings before interest and taxes/Total assets

X4 = Market value of equity/Book value of total debt

X5 = Sales/Total assets

Usually, the lower the Z-score, the higher the odds that a company is heading for bankruptcy. A Z-score that is lower than 1.8 means that the company is in financial distress and with a high probability of going bankrupt. On the other hand, a score of 3 and above means that the company is in a safe zone and is unlikely to file for bankruptcy. A score of between 1.8 and 3 means that the company is in a grey area and with a moderate chance of filing for bankruptcy.

"Ohlson Model uses a logit model to examine the effect of four basic factors on the probability of bankruptcy, the size of the firm, measures the firm's financial structure, measures the performance, and present liquidity. Nine financial ratios were chosen as independent variables to represent the four factors:"

O = -1.32 - .407X1 + 6.03X2 - 1.43X3 + .0757X4 - 2.37X5 - 1.83X6 + 0.285X7 - 1.72X8 - .521X9

X1 = ln(total assets/GNP price-level index).

X2 = total liabilities/total assets.

X3 = working capital/total assets.

X4 = current liabilities/current assets.

X5 = one if total liabilities exceed total assets, else zero.

X6 = net income/total assets.

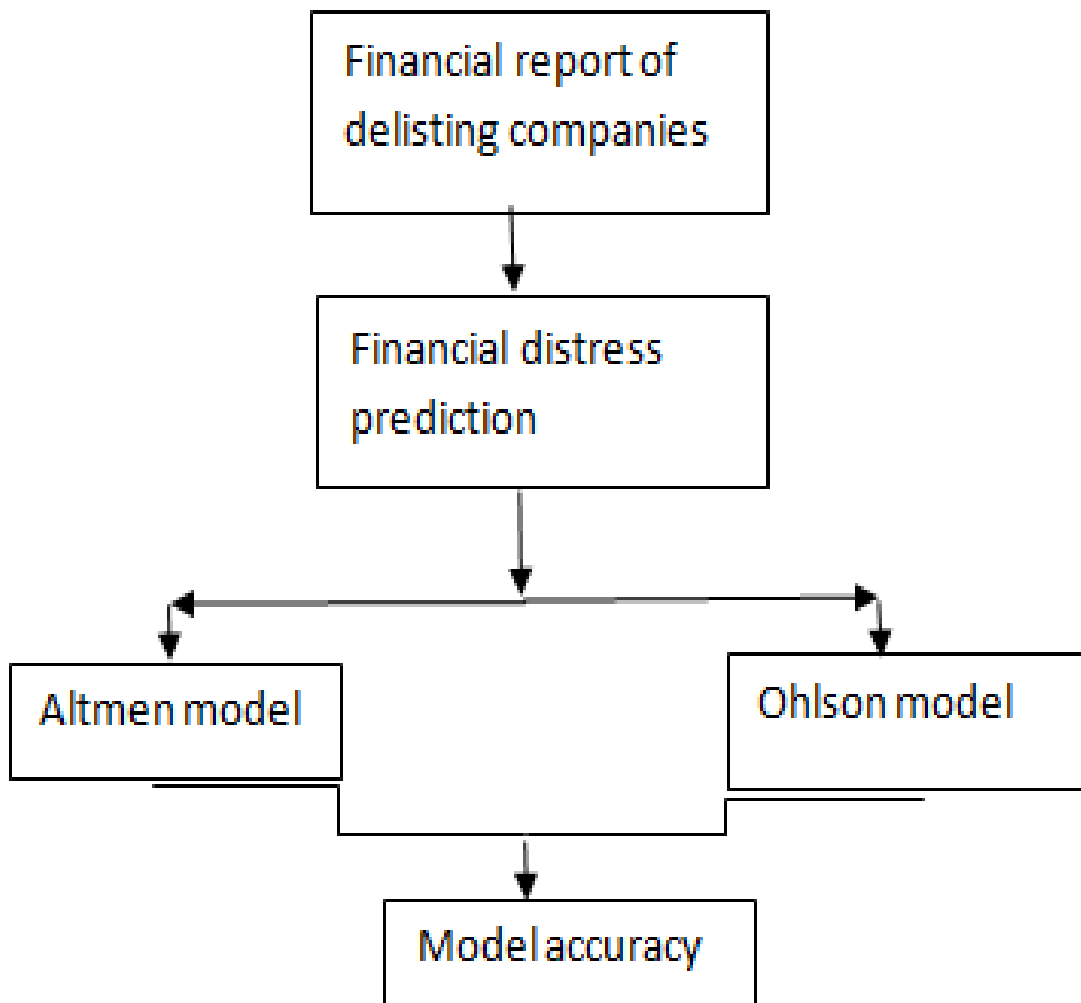X7 = funds provided by operations/total liabilities.

X8 = one if net income was negative for the last two years, else zero.

X9 = (NIt - NIt-1)/(|NIt| + |NIt-1|),

where Nit is net income for the most recent period. The denominator acts as a level indicator, and thus CHIN is intended to measure change in net income.

Comparison of Altman and Ohlson model

Figure 1. Research Model

Accuracy

Test the precision of the model used to answer by checking the values which is proposed in this study. The prediction results distress and not distress be determined by looking at a cut-off value on every model. Furthermore, to regulate the level of accuracy, is calculated by comparing the number of correct predictions by the number of samples. Here is the way to get a high degree of accuracy

Accureacy = (predictions correct / number of samples)*100

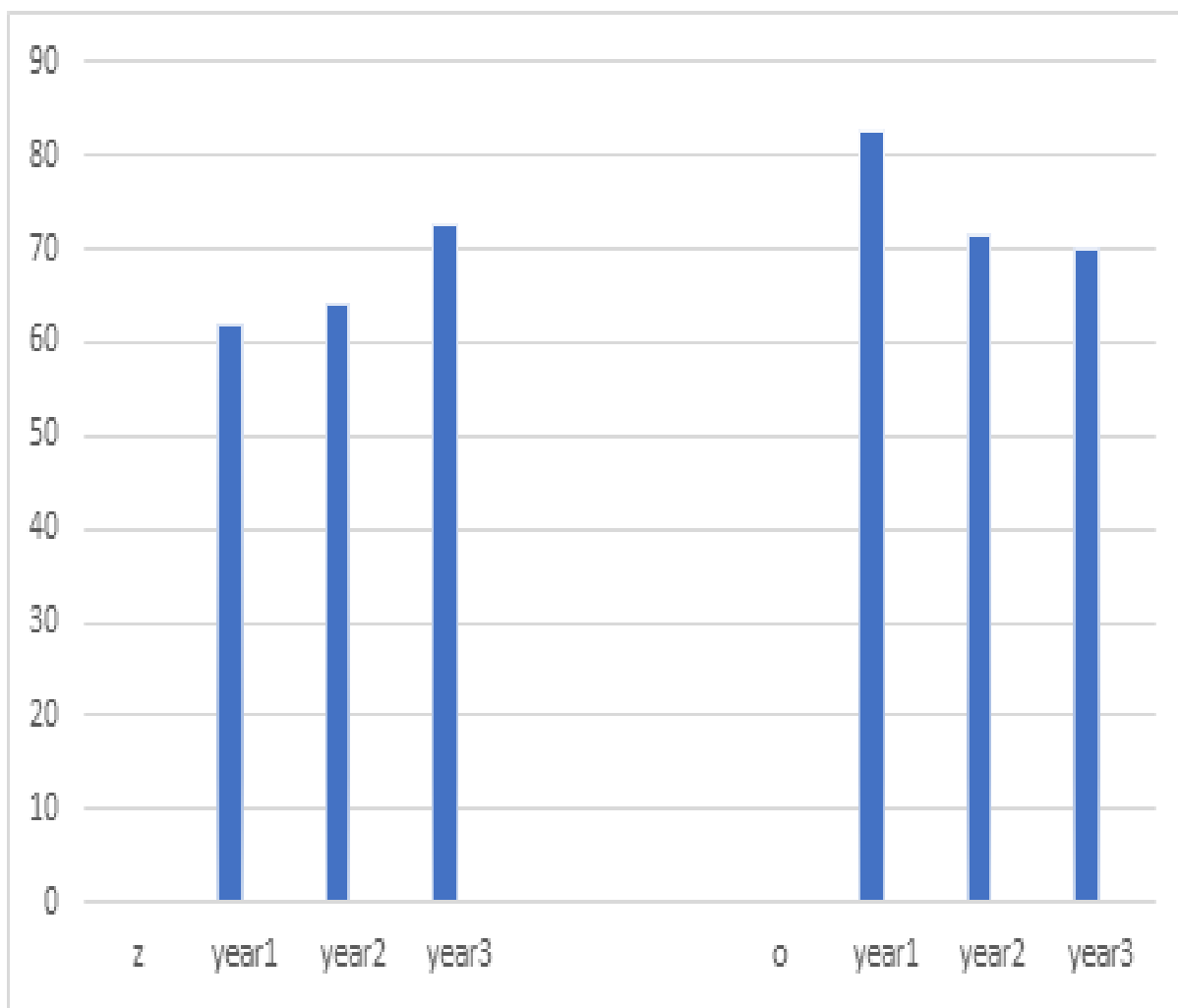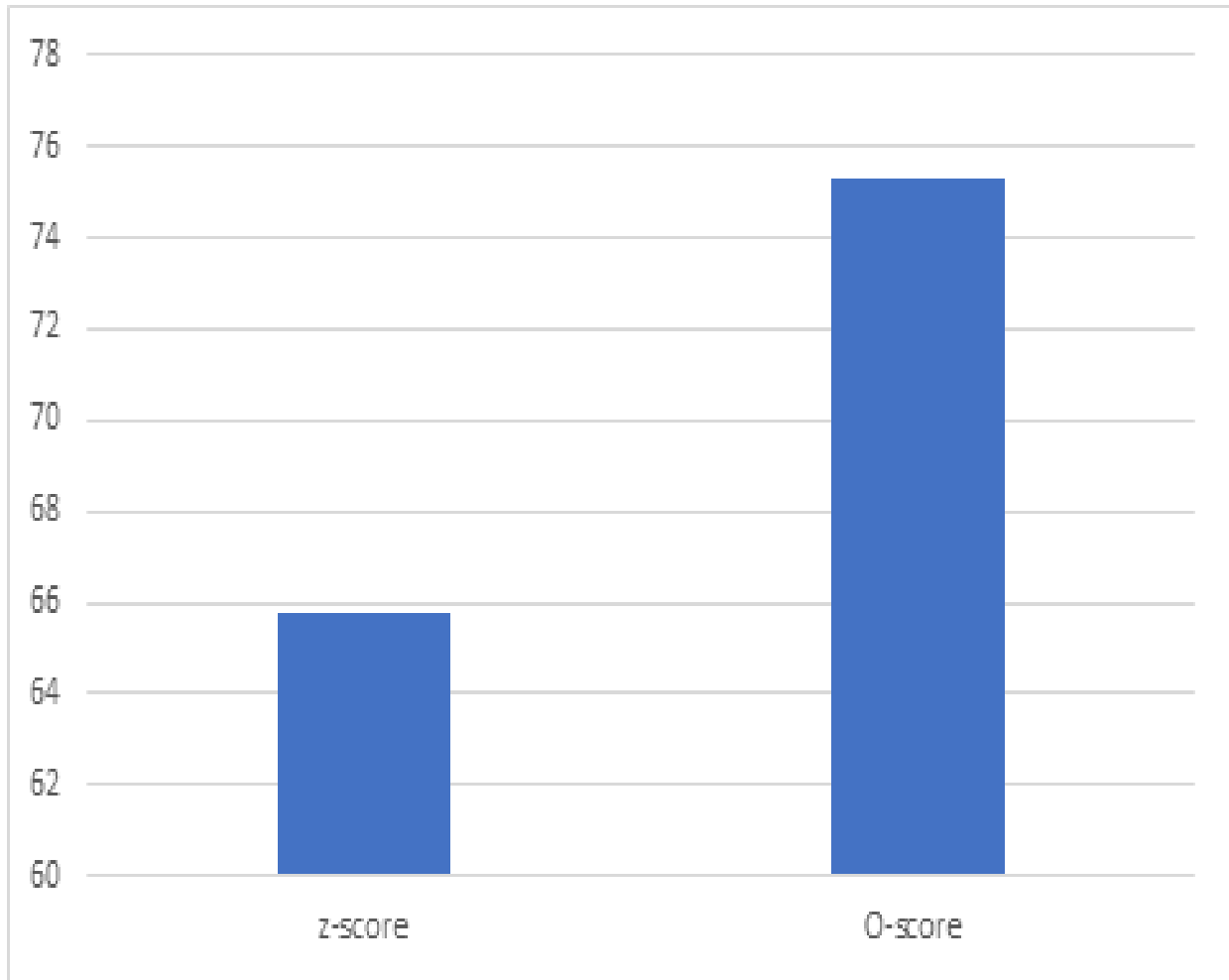**Figure1. Year wise comparison of Altmen(z-score) and Ohlson(O-score)**

Figrure1 showes that the year wise comparision between the altman and ohlson score in which they are ohlson was able to find more accuretly in the one year before the bankrupcy then the altman.

Figure2. Accracy of Altmen(z-score) and Ohlson(O-score)

The purpose of the figure 1and 2 is to show the reader an understanding of the distributions of the scores of Altmen and Ohlson. Useally representing scores of bankrupt and non-bankrupt companies, from the table 1 one can see the three zones of discrimination; the "safe" zone the "gray" zone and the "distress".

Table:1

Altman	Total companies	Distressed	%	ohlson	Total companies	Distressed	%
year1	29	18	62.06%	year1	29	24	82.75%
year2	28	18	64.28%	year2	28	20	71.4%

	22	16			20	14	
year3			72.22%	year3			70%
Total	79	52	65.8%	Total	77	58	75.3%

In table 1, the total performance of two models is presented. It is exciting to see that the model of Altman outperforms then Ohlson in the number of correct classifications for both type of companies, bankrupt and non- bankrupt in all time frames (years prior to bankruptcy). The accurateness in general tend to decrease as the years prior to bankruptcy increase. However, as can be observed from the table.

In the above table show accuracy of Altman model is 65.8 and Ohlson model has an accuracy of 75.3%. which shows that the Ohlson(O-score) models have the highest accuracy compared with the Altman (Z-score) in finding bankruptcy of companies.

The results suggested that the model of Ohlson executed better than the Altman. The deviance statistic test showed clear indications of the better fit of the model of Ohlson as the values for Altman were much larger thus indicating poorly fitting model. Also, from the results we could conclude that the models differ with their accuracy rate i.e. their predictive power is different to Indian firms

FINGING AND CONCLUSION
Taking a look at the outcomes from the Altman model which was presented in 1968 and without altering any of the factors and the coefficients, applying it to the 30 distinctive Indian organizations and figuring a normal of them, we can express that it can foresee insolvency with the exactness of 62.06%, 64.28% and 72.22% separately for first, second and third year before the date of insolvency. We can see that the outcomes may contrast dramatically from years to years and can frequently be deluding. Presently, contrasting this with the Ohlson model which was subsequently presented in 1980 and applying similar information from the past organizations. It can foresee insolvency with the exactness of 82.75%, 71.42% and 70% separately for first, second and third year prior to the date of liquidation. Thus, we can say that it has the most elevated likelihood to anticipating the liquidation, Here, we saw that even from three years prior it was giving the higher indications of liquidation and the outcomes didn't vary much all through the various years. It very well may be said that the Ohlson model ought to be liked and ought to be prescribed to financial specialists and organizations to foresee insolvency.

Presently, going to various perspectives, for example, anticipating it with the assistance of AI. The expectation of insolvency and accomplishing all that work physically is troublesome. subsequently, costing the significant season of financial specialists. A neural organization strategy has shown its capacity of tending to complex issues. A neural organization technique might have the option to upgrade a financial specialist's estimating capacity. For various exploration purposes, different models can be applied to look at the outcomes in various cases.

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