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Forecasting Financial Distress for Shaping Public Policy: An Empirical Investigation

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Abstract

Background: Prediction of financial distress has been made more accurate and reliable through machine learning methods. Financial stress affects the business corporate entity, society and the general economy. Analysing such nonlinear events is essential for preventing the dangers and supporting a favourable economic climate.

Objective: This paper seeks to develop a robust predictive model for identifying firms in the Indian context other than the financial service sector that may face financial distress and also to check the impact of one essential predictor, i.e., future cash flow, on financial distress prediction. Besides, the study also aims at making research that can inform public policy and provide recommendations.

Methods: The study employs financial information from the Prowess Database but is confined to non-financial service sector firms in India. Logistic regression, linear discriminant analysis (LDA), and artificial neural networks (ANNs) are applied to predict financial distress and their ability to foretell future cash flows. Other methods adopted in evaluating the models include accuracy, sensitivity, and specificity.

Results: ANNs outperform the other models based on accuracy and predictability, which are higher than the rates given by the other two models, namely logistic regression and LDA. The ANN model performs well in identifying financially distressed firms; thus, it is informative in evaluating their financial position. Also, results suggest that future cash flow substantially affects financial distress prediction, an essential new variable that needs to be considered in future research.

Conclusion: This predictive model of financial distress further gives a sound platform for the corresponding sector in India. In general, ANNs offer profound opportunities for managers, investors, policymakers, regulators and shareholders as an effective tool for preventive decision-making to reinforce the corporate world. This research demonstrates that high-level machine-learning approaches are still crucial in financial analysis and policymaking.

Index Terms

Forecasting; Public policy; Sustainability; ANN; Future cash flow; FCF; Logistic regression; LR; Linear discriminant analysis; LDA.

1 INTRODUCTION

Research into financial distress prediction (FDP) has become more popular during the recent financial crisis, bringing attention to the rising complexity and unpredictability of modern markets (Sethi et al., 2024). Academics, accountants, regulators, investors and companies are among the many organizations with vested interests in corporate bankruptcy and financial issue prediction. Promptly detecting any financial difficulties should be a top priority for all stakeholders. This study looks at the capacity of future cash flow analysis to forecast financial problems and inform public policy promoting economic stability.

When a company has trouble paying its bills and might go bankrupt, the corporate finance sector uses the phrase "financial distress" to characterize the scenario. Having dependable prediction models may assist investors in making more informed investment decisions and provide management with the necessary information to make course corrections. To more effectively protect the public interest and foster economic stability, it would be beneficial for regulators and legislators to become acquainted with indicators of financial distress.

Long before the company's decline, warning signs of financial instability may manifest. Various stakeholders may deliberately seek out these indicators to take precautions. Companies can reduce expenditures, restructure their debt or increase their capital. Investors may alter their portfolios to mitigate risk. Regulatory agencies may intervene and offer assistance promptly. In an effort to safeguard the economy, employment and investments, it is imperative to anticipate potential financial challenges. Traditionally, financial research has relied heavily on historical data.

The past is not always the most significant sign of the future regarding a company's success. Research suggests that potential cash flow analysis is one method to aid with future planning. "Cash flow" refers to the amount of money that remains after a business deducts its operational expenses. Estimates of future cash flow are crucial for predicting possible financial problems. A company's cash flow is the essence of the industry and is influenced by many financial decisions, financing activities and operational success. We also expect operational cash flow and accounting profits to affect future cash flows. According to Jemaa et al. (2015), one way to predict future cash flows is to look at accounting profits and operational cash flow. A better way to assess a company's financial health is via predictive models that look at future cash flows. Future cash flow analysis allows analysts to assess the viability of present operations and the capacity to meet long-term financial commitments by comparing the outcomes of three well-known models: logistic regression (LR), linear discriminant analysis (LDA) and artificial neural networks (ANN). This research uses cash flow projections as a proxy for financial health.

According to Krishnan and Largay (2000) and Farshadfar and Monem (2013), cash flows reveal whether a corporation can afford to pay dividends and investment returns. Because of this, the financial value model is quite concerned about this. Future financial flows, their influencing elements and the consequences of these findings should be thoroughly investigated under these conditions. This necessity motivates the promotion of research that centres on financial flows in the future.

A company's financial well-being is its capital flow, often known as its vitality. Looking at a company's cash flow projections for the future might give one a better idea of how well it can keep operations running and fulfil its obligations. Traditional financial problem prediction models such as LDA and LR have their limitations, but new opportunities for advancement have emerged with the advent of sophisticated machine learning (ML) approaches such as ANN. Logistic regression, a common statistical model, is straightforward to apply and comprehend. For a binary event, such as financial hardship, it examines a collection of predictor factors to determine the probability. Linear discriminant analysis, another time-honoured technique, aims to determine the best linear combination of features for classifying events into many categories. Both methods have been validated in several contexts and have a strong theoretical basis.

By integrating capabilities including self-organization, self-adaptation and real-time learning, ANNs aim to imitate how the human brain processes information (Zamani & Nadimi-Sahhraki, 2024). Taking their design cues from how the human brain functions, ANNs have revolutionized predictive modelling. However, their implementation requires a great deal of computational power and expertise to discover complex, nonlinear relationships in data, which might enhance the predictive abilities of ANNs.

Since the 1960s, there has been considerable interest in predicting potential bankruptcy of financial institutions (Altman, 1968). The degree of attention that a nation devotes to this matter indicates its economic strength and advancement (Zopounidis & Dimitras, 1998). The two primary categories of bankruptcy prediction models are statistical and artificial intelligence (AI) methodologies. The actual use of statistical approaches is restricted by assumptions such as normalcy, linearity and independence among predictor variables and pre-existing functional forms linked to the criteria and predictor variables (Hua et al., 2007). Numerous AI-based studies have been conducted in the past decade to predict bankruptcy. Apt algorithms are utilized, including artificial neural networks, genetic algorithms and decision trees. Consequently, examining the non-financial service industry in India is also worthwhile.

Thus, this study aims to evaluate LR, LDA and ANNs for their ability to foretell future cash flows and, by extension, financial difficulties. This study compares and evaluates different models to provide thorough insights that can influence public policy and corporate strategy. Economic systems may become more robust if our results are used to improve financial predictive analytics. Our comparison and assessment of several models provide comprehensive insights that might affect public policy and business strategy. Applying the findings of this work to enhance financial predictive analytics has the potential to make economic systems more resilient.

The rest of the article is organized as follows. The literature review lays out the background and purpose of the research in Section 2, while Section 3 details the methods used, where the data came from, a summary of the variables and the empirical model. Section 4 delves into the analysis and research results. Section 5 covers the study discussion. Section 6 provides the conclusion, policy implications, and limitations with future research directions.

2 LITERATURE REVIEW

Financial failure is defined as a situation in which a company's liabilities exceed its assets or it experiences severe and persistent losses (Hua et al., 2007). Common causes and symptoms of financial failure include a lack of financial expertise, insufficient capital planning, poor debt management, insufficient protection from unanticipated occurrences and issues with effective operational discipline o the financial market. Accurate representation of the above characteristics in a company's financial accounts is frequently the foundation of bankruptcy prediction.

In the late 1960s, Altman (1968) created the first model for predicting insolvency using many variables. Researchers in the fields of banking, finance and credit risk all across the globe began using the multivariate method for failure prediction after this ground-breaking study. Banks, investors, asset managers, rating agencies and even troubled firms rely on failure prediction models. Various classification methods have been suggested to predict financial hardship using ratios and data extracted from these financial statements. These methods encompass, but are not restricted to, the following: multivariate approaches, linear multiple discriminant approaches (MDA) (Altman, 1968; Altman et al., 1977), multiple regression (Meyer & Pifer, 1970), logistic regression (Dimitras et al., 1996), factor analysis (Blum, 1974), stepwise (Laitinen & Laitinen, 2000) and univariate approaches (Beaver, 1966). However, conventional statistics are of limited practical utility because they are predicated on rigorous assumptions regarding linearity, normality, predictor variable independence and a pre-existing functional form between the criteria and predictor variables (Hua et al., 2007). Appiah et al. (2015) conducted a comprehensive literature review to facilitate the understanding of methodological challenges associated with conventional statistical methods, artificially intelligent expert systems and theoretical approaches to resolving the business failure syndrome. Even though there is a significant quantity of research into business failure prediction, stakeholders continue to require a straightforward, precise, theoretically sound and widely implemented model.

Elhoseny et al. (2023) investigated a novel financial distress prediction model developed using an adaptive whale optimization algorithm with deep learning (AWOA-DL) approach, utilizing a dataset featuring 307 non-insolvent and 383 bankrupt samples and found that the AWOA-DL approach demonstrated superior performance compared to the other evaluated methods. On the other hand, Singh and Mishra (2016) used the logit technique to estimate y-scores with a sample of 208 companies from India. Agarwal and Maheswari (2015) examined the Merton distance-to-default (DD) as a default predictor for a subset of listed Indian companies while applying logistic regression and multiple discriminant analysis. They found that option-based distance-to-default (DD) is statistically significant in predicting defaults and has a strong negative correlation with the default likelihood.

Mishra et al. (2021) attempted to develop a model for predicting bank insolvency and compare it with three other models using 75 Indian banks as a sample to predict the financial difficulties of commercial banks. They found that the ANN prediction model produces more precise predictions. On the other hand, Shrivastava et al. (2018) conducted an investigation into the prediction of corporate financial distress in the Indian corporate sector by employing Bayesian and standard logistic regression and discovered that Bayesian methodology possesses superior predictive capabilities. In addition, Balasubramanian et al. (2019), developed a corporate distress prediction model for listed Indian companies using financial and non-financial parameters while applying conditional logit regression techniques and found that models including financial factors had an accuracy of 85.19% and 86.11% for predictions. In comparison, models including both financial and non-financial variables had an accuracy of 89.81% and 91.67%, respectively, which is a relatively superior performance. Singh and Singla (2023) used up-to-date data to re-estimate the coefficients of Altman's model and created a new model for predicting financial hardship using logistic regression. To better anticipate financial hardship and prevent future insolvency, they discovered that the newly constructed model had attained better predictive accuracy than the re-estimated model. Additionally, methodological challenges associated with models that predict business failure has been extensively documented in numerous studies. For instance, Scott (1981), Zmijewski (1984), Taffler (1985), Altman (1984), O'Leary (1998), Keasey and Watson (1991), Altman and Narayanan (1996), Dimitris et al. (1996), Morris (1997), O'Leary (1998), Tay and Shen (2002), Aziz and Dar (2006), Balcaen and Ooghe (2006) and Kumar and Ravi (2007) are all included.

A company's cash flow is the inflow and outflow of funds during a specific period, while its future cash flow is the sum of all of its anticipated revenues and expenditures. An essential financial indicator, cash flow indicates a company's capacity to bring in and spend money. It is possible to compute future cash flows using the same formula as previous ones. Numerous studied have been based on cash flow impact on financial distress. For instance, Phan et al. (2022) investigated the influence of cash flow on financial distress among privately listed Vietnamese firms. The study found a negative correlation between cash flow from operations and from financial activities. In the same vein, Catanach (2000) argued that operating cash flows (OCF) is a reliable indicator of financial institution distress, as it represents the actualized operational risks of these companies. They concluded that OCF did not enhance overall classification accuracy in most models evaluated after examining the relationship between OCF and institution risk using a latent variable modelling strategy. Additionally, Safiq et al. (2020) examined the effects of financial and non-financial variables on the financial distress of Indonesian companies and discovered that future cash flow significantly affects financial distress.

Focusing on the Indian aspect of research, Murty and Mishra (2004) examined the impact of cash flow ratios on financial distress prediction. On the other hand, Kumar and Ranjani (2018) examined the financial constraints of Indian manufacturing enterprises by studying the sensitivity of cash flow to investment. They discovered that financial constraints were significant only for firms with modest market capitalization. As we can see from the above literature review, only a few papers have focused mainly on the context of cash flow. However, we have not found a paper that would mainly measure the impact of future cash flow on financial distress prediction in the Indian corporate sector, which is a novel contribution of our study.

It is clearly concluded from the above literature review that there is a gap in the methodological perspective. Numerous studies have been made in the past, but research has yet to focus on the specific impact of future cash flow on financial distress prediction with an assessment of comparative viewpoints, particularly based on logistic regression (LR), linear discriminant analysis (LDA) and artificial neural networks (ANNs). Therefore, this study will investigate the above gap and address this concern. We also take other financial ratios into the analysis of future cash flow to check the impact. This will give a new direction to organizations and demonstrate the importance of the impact of future cash flow on the prediction of company distress, particularly on the aspects of non-financial service sector Indian firms. A company's ability to pay its bills, keep operations going and stay out of bankruptcy depends on its future cash flow, which is especially important when times are financially tough. Stable, predictable financial inflows improve the company's chances of survival and recovery by allowing strategic planning, debt restructuring and creditor discussions. The reason behind choosing the service sector firms is that the service sector is the backbone of the Indian economy, especially in gross domestic product (GDP). Lots of employees work in this sector compared to others. To see whether the GDP percentage is good from the service sector perspective, a prediction model is necessary with a particular focus on the importance of future cash flow in financial distress prediction. Before any finance-related problems occur, a proper study is necessary for providing an early alarm. In conclusion, the present study will summarize the implications and contribution to public policy, by which it stands out from earlier studies.

2.1 Study objective and rationale

The primary objective of this research is to conduct a comparative assessment to determine the influence of future cash flow on the prediction of financial distress and to develop an early warning model for Indian non-financial service sector firms. Finally, the contribution to the development of public policy is defined.

Based on the above literature gap, the study has the following objectives:

1. To determine the impact of future cash flow on predicting financial distress.

2. To suggest the most precise model for the effective prediction of bankruptcy for Indian non-financial service sector firms based on the analysis.
3. To determine the study's role in shaping public policy theoretically.

The broad objective of the investigation is to explore the collection of information that corporations and investors find intriguing. This research is vital because it sheds light on future cash flow patterns and connects the dots between public policy and forecasting of financial trouble. To stabilize economies, safeguard stakeholders and guarantee long-term financial health, authorities must be able to anticipate possible financial difficulties.

The study aims to address the subsequent research questions:

1. Is there any significant relationship between future cash flow and financial ratios towards financial distress?
2. Is the classification accuracy of the LR, LDA and ANN models significantly different?
3. Which are the most important predictors among them?
4. Does this study have a particular implication or contribution toward strengthening public policy?

3 RESEARCH METHODOLOGY

3.1 Data source

An ideal area for future study would be the need for prediction studies in developing economies. Citations from earlier works (Claessens et al., 2000; Liu, 2015) highlight the shortcomings of corporate governance in Asian countries. Because of India's status as a rising economy, which draws investments from all around the globe, we focus on that country. Businesses and corporations in the service industry may use our findings to anticipate better when they may have financial difficulties or bankruptcy, which will improve their ability to make decisions.

As India's most significant corporate sector, the service sector is essential. We have collected data from CMIE PROWESS, an Indian corporate database. Our investigation of Indian firms encompassed different subsectors of the service sector, including business services & consultancy, computer software, diversified non-financial services, education, hotels & restaurants, ITES, media & broadcasting, retail trading, transport infrastructure services, storage & distribution, telecommunication services, tourism, transport logistics services, wholesale trading and other miscellaneous services. We randomly selected companies in the service sector, except the financial service sector. We are not taking the financial service sector into consideration because of its complex rules, critical legal structures and regulations. We took 4,500 firm-years for nine years as a sample covering important subsectors within the service sector. Finally, we deducted the missing data area and after taking the logarithm, 830 firm-years were taken as our final observation for the analysis. The research employs nine years of data from 2012/2013 to 2020/2021. Rigorous data refinement was used to assure the quality of the study, resulting in a decrease from 4,500 to 830 firm-years. Only credible and complete data points were retained once missing data were identified and removed to minimize biases and errors. A logarithmic transformation was applied to the dataset to isolate the most statistically significant observations further. The significance of data integrity is highlighted by this significant decrease, which must be met to guarantee that the final sample is representative and can provide strong, valuable insights for the study of important service sector subsectors over the nine years.

3.2 Variables

A comprehensive literature analysis was undertaken to determine whether financial ratios are used to forecast business insolvency. Sehgal et al. (2020) proposed several measures for bankruptcy prediction, roughly categorizing them as growth, liquidity, profitability, leverage and market ratios. Altman's (1968) research also used specific chosen ratios. In the same vein, Soni (2019) used different ratios for financial distress prediction of manufacturing firms. We started by gathering data for an empirical study on 12 different variables, which are all financial ratios. A multi-stage refining and removal procedure was used to identify the most essential causes of financial distress. This is due to data discrepancies, missing values, few data points for specific years or strong correlations across variables. Finally, five variables were considered for analysis purposes.

Table 1 displays all of the financial ratios that were chosen for analysis. Figure 1 depicts the research framework of this study. There are five independent variables and one dependent variable, i.e., financial distress. The liquidity category contains three ratios. First, the role of cash operating activities is to evaluate the strength of the firm in generating cash within the course of business operations so as to be in a position to meet its short-term obligations (Billah et al., 2015; Prabhakar & Japee, 2023; Michalski, 2013). Insight into a company's ability to meet current obligations without incorporating inventory can be observed through the quick ratio, which compares liquid assets to current callable obligations. Future cash flow is a thoroughly analysed projection of the stream of cash that is expected to flow in the future and a firm's ability to support these flows where needed. The measurement CFOt+1 represents the expected cash flow from operations (CFO) for the next period, typically one year ahead. It is a forward-looking metric to estimate an organization's operational cash-generating capacity in the upcoming period (t+1). In the profitability category, net working capital shows the ratio of short-term assets to short-term liabilities and thus depicts the firm's efficiency in liquidity and operational areas (Firmansyah et al., 2018; Lukic, 2023). Finally, there is net profit before tax, also known as trading profit or operating profit, which gives a direct picture of the company's profit-making capability, neglecting the taxation aspect. Both these ratios combined give an all-round financial health status of a business.

Table 1. *Summary of variables.*

Category	Ratio	Definition
Liquidity	Cash flow from operating activities	NI + NCI+ CWC
Liquidity	Quick ratio	CA-INV-PE / CL
Liquidity	Future cash flow	CFOt+1
Profitability	Net working capital	CA - CL
Profitability	Net profit before tax	TR - TE

Notes: NI: net income, NCI: non-cash items, CWC: changes in working capital, CA: current assets, INV: inventory, PE: prepaid expenses, CL: current liabilities, CFO: cash flow from operations, TE: total expenses, TR: total revenue. All variable measurements are taken on the basis of past reference (Sehgal et al., 2020; Isayas 2021; Safiq et al., 2020).

3.3 Distress measurement criteria

In order for a company to be considered distressed, according to Foster et al. (1998), one of four things must be true: negative working capital in the current year, operating loss in the three years preceding the event year, retained earnings deficit for the year preceding the event year, or net loss in one or more of the last three years preceding the event year. We used criteria consistent with Foster et al. (1998) to quantify distress.

3.4 Empirical methodology

Financial distress prediction models are built and compared in this work using three models for bankruptcy prediction: LR, LDA and ANN. The Indian database does not make extensive use of the most popular models for forecasting financial hardship, including LR (Lin, 2009; Ohlson, 1980), ANN (Chen & Du, 2009; Geng et al., 2015; Lin, 2009) and LDA (Altman et al., 1994). In Indian research, LDA has rarely been employed as a prediction model. Many studies have discovered that LR provides better prediction results than the other quantitative models, even if much of the current research suggests that the ANN model is more resilient and accurate (Kumar et al., 1995). When Eftekhar et al. (2005) evaluated the accuracy of logistic and ANN models with multivariate LR models, the logistic model was more accurate in 68% of the situations.

Some studies claim that LR is the most accurate of the current models (Kristanti & Dhaniswara, 2023; Kumar et al., 1995; Eftekhar et al., 2005) but some say that the ANN model is the most resilient (Mishra et al., 2021; Kasgari et al., 2013). We employ three models—LR, ANN and LDA—to determine which provides the most accurate predictions in the Indian environment. A brief overview of these techniques is shown here.

The logistic regression method uses independent variables to determine the likelihood of an event, such as voting or not voting, presence or absence of a disease. Classification and predictive analytics often use this statistical model, also called a logit model. The dependent variable can only take values between 0 and 1 since the result is a probability. The odds, or the likelihood of success divided by the probability of failure, are transformed via a logit transformation in logistic regression. The following formulae express the logistic function, which is sometimes called the log odds or the natural logarithm of odds:

$$logit(pi) = 1/(1+ exp(-pi))$$

$$ln(pi/(1-pi)) = Beta\_0 + Beta\_1*X\_1 + \dots + B\_k*K\_k$$

Here, x is the independent variable and *logit(pi)* is the dependent or response variable in the logistic regression equation. Most often, maximum likelihood estimation (MLE) is used to estimate the beta parameter, also known as the coefficient, in this model.

Logistic regression models are used to study the impact of predictor variables on categorical outcomes. For binary outcomes, such as non-Hodgkin's lymphoma, the model is referred to as a binary logistic model (Nick and Campbell, 2007). An example of a multiple or multivariate logistic regression model would consider risk factors and treatments as predictors. This research uses a binary outcome variable, where 0 indicates that the firm is not in financial hardship and 1 indicates that it is. Our logistic regression (LR) model is best understood as:

$$Financial\ distress\ (FD) = \beta 0 + \beta 1(CFO)1it + \beta 2(QR)it + \beta 3(FCF)it + \beta 4(NWC)it + \beta 5(NPBT)it + \mu it \quad (1)$$

Like multinomial logistic regression analysis, discriminant analysis uses latent variables to make multivariate predictions about group membership (Johnston, 2024). As a statistical tool, discriminant analysis may divide data into predetermined categories according to their traits. It determines the optimal set of criteria for categorization. Many industries may benefit from this, including healthcare (disease diagnosis), marketing (customer segmentation) and banking (credit risk assessment). Scores are assigned to observations using the model discriminant functions. A higher score suggests a greater likelihood of becoming a member of that specific group. Logistic regression has always been the approach of choice for binary or two-class classification issues. If there is a clear division among the classes, it might become unstable. Since LDA considers these concerns, it is the best linear approach to use. It mimics the behaviour of a set of linearly related coefficients. This study's LDA model is best described as:

$$Z = \beta 0 + \beta 1(CFO)1it + \beta 2(QR)it + \beta 3(FCF)it + \beta 4(NWC)it + \beta 5(NPBT)it + \mu it \quad (2)$$

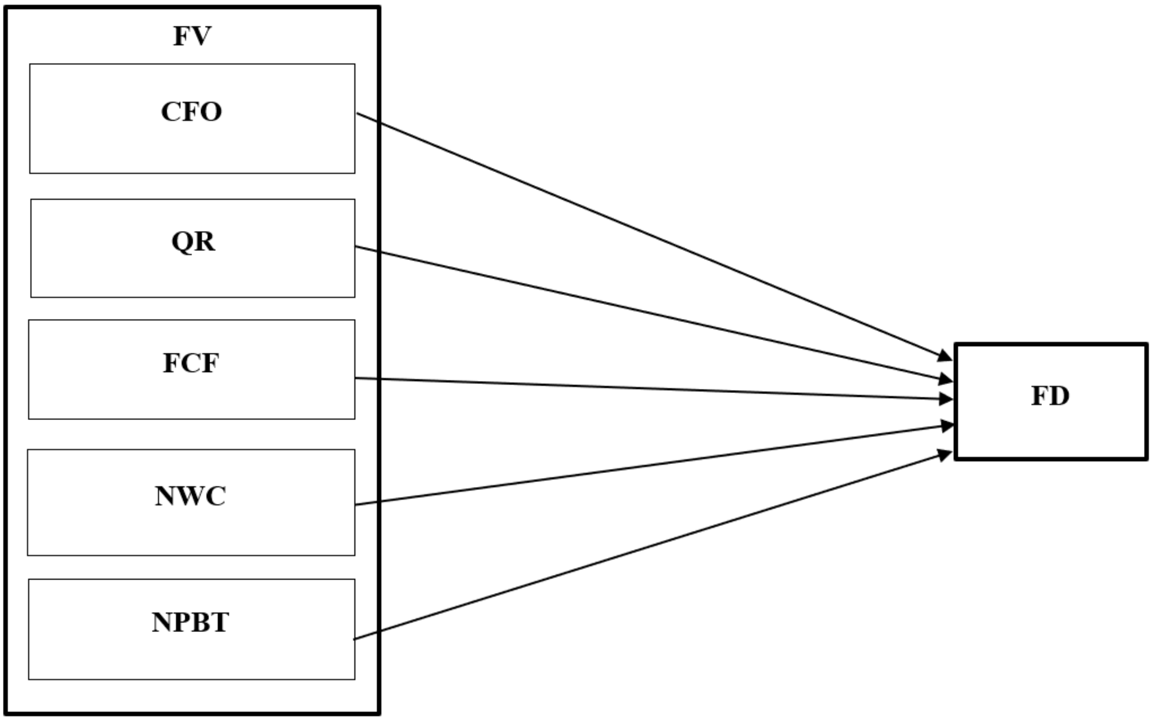

Figure 1. *Study Framework.*
Notes: FV: financial variable, CFO: cash flow from operation, QR: quick ratio, FCF: future cash flow, NWC: net working capital, NPBT: net profit before tax, FD: financial distress.

The artificial neural network (ANN) is an example of a computational model that draws inspiration from the human brain. ANNs are composed of layers of linked neurons. They undergo a training procedure that involves modifying the weights between neurons to improve their prediction and classification abilities.

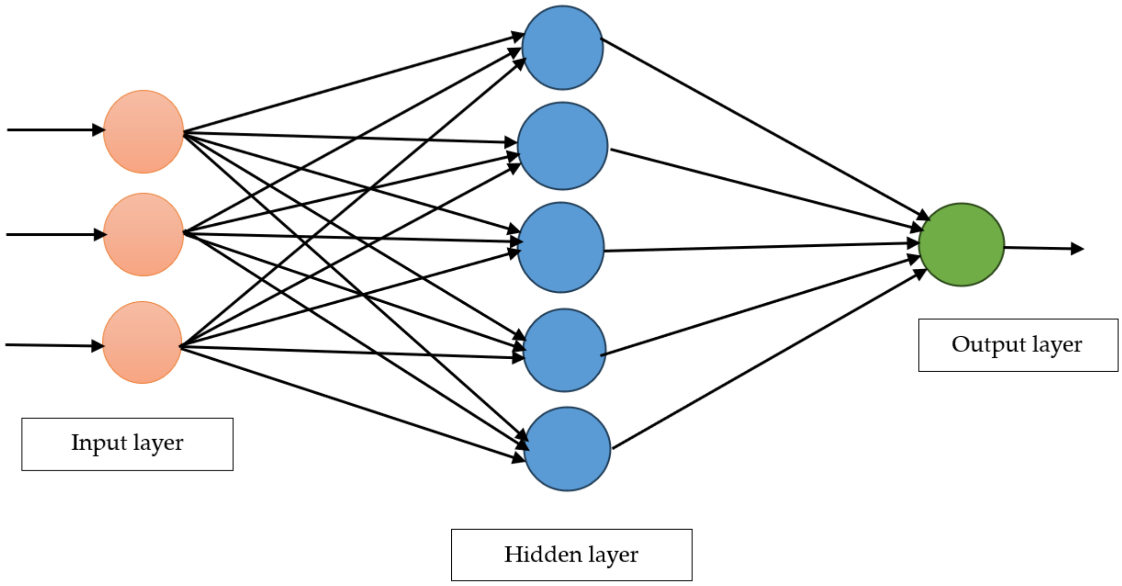

Figure 2. *Single hidden layer ANN architecture.*

While artificial neural networks shine in complex identification tasks, deep learning models now drive artificial intelligence progress. In recent years, there have been immense advances in networks with hidden layers that analyse vast troves of data. However, constructing such complex architectures requires considerable effort and large datasets. Artificial neural networks can assimilate nonlinear relationships within information, lending themselves to pattern recognition (Anandarajan et al., 2001). A neural network merges interconnected layers of computational neurons into sophisticated designs. One prevalent structure, multilayer perceptron, arranges nodes across tiers in a hierarchical fashion. Such multilayer networks stack an input layer, an output layer and one or more hidden intermediate layers. The number of neurons distributed amongst the layers and how many layers exist determines classification accuracy, as earlier work elucidated (Anandarajan et al., 2001). Advanced bankruptcy prediction and further plans for corrective action would gain from an early predictive model with ANNs. Figure 2 lays out an ANN model with only one hidden layer.

The dataset is divided into two based on a train-test ratio of 70:30 to fulfil the given objectives. Numerous academic papers and analyses (Salcedo et al., 2016; Hosamani et al., 2020; Sharma & Goyal, 2015) have established that a 70:30 split provides the ideal balance. The precision of each forecasting model will be decided by implementing it on separate training and testing data. We compare the confusion matrices of our models on the test samples.

All three models use the same set of five ratios as inputs. The following ratios are considered:

(a) cash flow from operation,

(b) quick ratio,

(c) future cash flow,

(d) net working capital,

(e) net profit before tax.

Based on how well each neural network performed on the testing set, the number of hidden layers and neurons in each layer of the ANN model is chosen. The experimental selection of momentum, learning rate and neuron number is carried out. An input layer, one or more hidden layers and an output layer are the building blocks of a multilayer perceptron (MLP), a specific kind of artificial neural network. The activation function is nonlinear and used by every neuron in the network. Pattern identification and classification challenges are where MLPs shine (Altman et al., 1994). The six inputs in our research are activated by a hyperbolic tangent in the hidden layer and a softmax in the output layer. We apply each prediction model to the train-test dataset and then we calculate the model accuracy. The model test sample confusion matrices are compared.

4 ANALYSIS

4.1 Descriptive statistics

Descriptive statistics provide summary information on the distribution and main trends of the variables mentioned in Table 1. Table 2 provides the descriptive statistics. There is a lot of variation in LN_QR, which varies from -4.61 to 5.94, with a standard deviation of 1.50662 and a mean of -0.1932. With a range from -4.61 to 9.13, LN_FCF has a wide range of values, with a mean of 1.6209 and a more significant standard deviation of 2.66168. Meanwhile, -12,587.87 and 9,411.61 are the extreme values of NWC, with a mean of -2.0737 and a significant standard deviation of 604.56242. Between -3,670.00 and 4,149.60, the range of NPBT is 266.29041, with a mean of 14.9992. LOG_CFO ranges from -2.00 to 3.96, with a mean of 0.6766 and a standard deviation of 1.15909. FD has a mean of 0.33 and a standard deviation of 0.471; it is a binary variable with 830 observations.

4.2 Correlation and multicollinearity statistics

The correlation matrix shows several noteworthy associations between the variables. There is a thin inverse relationship between LN_QR and both LN_FCF (-0.048) and FD (-0.243). A minor negative correlation with FD (-0.070) and substantial positive correlations with LOG_CFO (0.885) and NPBT (0.268) are seen for LN_FCF. NWC is somewhat positively correlated with LN_QR (0.128) and somewhat negatively correlated with NPBT (-0.185) and LOG_CFO (-0.132). Between NPBT and LOG_CFO, there is a moderate positive correlation of 0.268 and a weak negative correlation of -0.169. A modest negative correlation of -0.056 exists between FD and LOG_CFO. The statistical analysis shows that most associations are significant ($p < 0.05$).

Table 2. *Descriptive statistics.*

	N	Minimum	Maximum	Mean	Std. deviation
LN_QR	2761	-4.61	5.94	-0.1932	1.50662
LN_FCF	1485	-4.61	9.13	1.6209	2.66168
NWC	2939	-12,587.87	9,411.61	-2.0737	604.56242
NPBT	2194	-3,670.00	4,149.60	14.9992	266.29041
LOG_CFO	1392	-2.00	3.96	0.6766	1.15909
FD	2898	0	1	.33	.471
Valid N (listwise)	830				

In the case of multicollinearity, our VIF is less than 10 as mentioned in Table 3, which reports the correlation and multicollinearity statistics. The tolerance value is greater than 0.1, which indicates that we have no multicollinearity issue in this study, and our result is also supported by past literature (Tinoco & Wilson, 2013; Neter et al., 1983; Htet & Oo, 2024). The condition index (CI) is also less than 15 and all the correlation coefficients are below 0.90 in our study, indicating that no multicollinearity exists (Senaviratna & Cooray, 2019; Midi et al., 2010).

4.3 Logistic regression

A binary indicator of financial difficulties serves as our dependent variable. A corporation is assigned a value of 1 if it shows signs of financial trouble and a value of 0 if not. For this research, we used five different ratios as independent variables. The first step in anticipating financial hardship and its influence on ratios used to measure it is to apply the LR model. The results of the LR analysis are depicted in Table 5.

The liquidity ratio of cash flow from operating activities has a positive insignificant relationship with financial distress, which means that the LOG_CFO ratio has no significant impact on financial distress. However, the quick ratio variable has a negative and significant relationship with financial distress, which means that increasing the quick ratio will decrease the possibility of financial distress. On the other hand, the probability of financial difficulty will decrease due to an increase in the liquidity ratio of future cash flows, as there is a negative significant correlation between the two. Future cash flows are vital for gauging impending financial trouble because they indicate an enterprise's capability to create sufficient earnings to satisfy its obligations. Positive liquidity denotes that the company can pay its operating costs, debt obligations and other responsibilities, reducing the hazards of financial distress. In contrast, negative cash flows communicate possible short-term financial difficulties and instability that may surface.

Table 3. *Correlation and multicollinearity statistics.*

		LN_QR	LN_FCF	NWC	NPBT	LOG_CFO	FD
LN_QR	Pearson correlation	1					
	Sig. (2-tailed)						
LN_FCF	Pearson correlation	-0.048	1				
	Sig. (2-tailed)	0.073					
NWC	Pearson correlation	0.128**	-0.118**	1			
	Sig. (2-tailed)	0.000	0.000				
NPBT	Pearson correlation	0.036	0.268**	-0.185**	1		
	Sig. (2-tailed)	0.103	0.000	0.000			
LOG_CFO	Pearson correlation	-0.069*	0.885**	-0.132**	0.268**	1	
	Sig. (2-tailed)	0.010	0.000	0.000	0.000		
FD	Pearson correlation	-0.243**	-0.070*	0.007	-0.169**	-0.056*	1
	Sig. (2-tailed)	0.000	0.012	0.746	0.000	0.049	
	VIF	1.044	4.262	1.089	1.169	4.296	
	Tolerance	0.958	0.235	0.918	0.855	0.233	
	CI	1.556	1.621	2.022	2.882	6.591	

Notes: ** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

Table 4. *Omnibus tests of model coefficients.*

	Chi squared	Df	Sig.
Step	249.496	5	0.000
Block	249.496	5	0.000
Model	249.496	5	0.000

Table 5. *Variables in equation.*

Variables	B	Std. error	Wald	Sig.	Exp(B)
LN_QR	-0.590	0.085	47.714	0.000	0.554
LN_FCF	-0.163	0.074	4.825	0.028	0.849
NWC	-0.002	0.001	4.215	0.040	0.998
NPBT	-0.023	0.004	28.026	0.000	0.978
LOG_CFO	0.345	0.183	3.563	0.059	1.411
Constant	-1.098	0.131	70.047	0.000	0.334

Table 6. *Hosmer-Lemeshow test.*

Chi squared	Df	Sig.
5.164	8	0.740

Table 7. *R-squared.*

-2 log likelihood	Cox & Snell R-squared	Nagelkerke R-squared	McFadden R-squared
718.515	0.260	0.377	0.258

Table 8. *Classification matrix for LR.*

Classification table					
Observed			**Predicted**		
			Financial distress		**Percentage correct**
			Non-distress	**Distress**	
Step 1	**Financial distress dummy**	**Non-distress**	572	34	94.4
		Distress	133	91	40.6
	Overall percentage				79.9

By reviewing projected cash flows, interested parties can evaluate an organization's monetary well-being, foresee issues as they may develop and execute remedial actions. Consequently, anticipated liquidity is a pivotal measure for judging an enterprise's sustainability and economic resilience through periods that may challenge even the most well-established companies. By considering this key evaluation point attentively, stakeholders can help direct firms to choose strategies to preserve long-term financial security despite unforeseen macroeconomic fluctuations or unexpected complications.

Although a decline in the profitability of net working capital is positively correlated with impending financial trouble, maintaining a solid net working capital ratio can provide a protective buffer against distress. In fact, the ratio is strengthened, which reduces vulnerability, as a reservoir of net working capital improves liquidity, enabling simpler coverage of impending costs and continuation of stable operations. In contrast, a depletion may indicate that the organization is having difficulty meeting its urgent financial obligations and might put at risk its sustainability in the absence of capital investment. Stability is promoted and illiquidity-related complications are prevented by prudently maintaining sufficient net working capital. On the other hand, a negative significant relationship exists between the profitability ratio of profit before interest and tax and financial distress. Specifically, increasing the profit before interest and tax ratio will reduce the likelihood of financial distress. By increasing a company's profitability, which allows it to pay interest expenditures and operating costs, a rise in PBIT (profit before interest and tax) alleviates financial strain and improves financial stability.

The omnibus test in logistic regression is a complex statistical process determining whether the overall predictive model demonstrates substantially greater explanatory power than a null hypothesis proposing no association between factors. In other words, it assesses whether any independent variables within the model exert significant influence over variations in the dependent construct after accounting for all other incorporated variables. In our study results, it is significant with a p-value of less than 0.05. Table 4 reports the omnibus test of model coefficients. On the other hand, the Hosmer-Lemeshow goodness-of-fit test evaluates logistic regression models by comparing predicted and actual outcomes. For this analysis, the high p-value of 0.740 indicates a negligible discrepancy between expected results based on the model and the actual observed data, underscoring an excellent fit depicted in Table 6, which reports the Hosmer-Lemeshow test results. By convention, p-values above 0.05 signify that differences between prediction and observation are likely due to chance rather than a flawed model, so the null hypothesis that the logistic regression suitably accounts for patterns in the data cannot be rejected (Hosner et al., 1997). Thus, with a p-value exceeding the statistical significance threshold, it is reasonable to rely on this model's predictions of the dependent variable, given the specified predictor variables, as the regression appears to have reliably learned the relationships in the dataset.

More specifically, while building a logistic regression prediction model, it is essential to provide the outcome percentage and a conservative estimate of the model's overall fit, as assessed by the Cox-Snell R-squared (percentage of variance explained) (Cox & Snell, 1989; Magee, 1990). The Cox-Snell R-squared, derived from the likelihood ratio, is employed to modify the maximal likelihood estimate. However, it is not permitted to exceed a value of less than 1. The value in this particular instance of our investigation is 0.260. The Nagelkerke R-squared converts the Cox-Snell R-squared into a numeric value between 0 and 1 to enhance its interpretability. The Nagelkerke R-squared is 0.377. The Last-McFadden R-squared, similar to the conventional R-squared from linear regression, contrasts the model probability to that of a null model. Nevertheless, it typically yields significantly lower results. The result is 0.258. The positive R-squared values of all three models indicate a satisfactory match, which are depicted in Table 7, reporting the model summary of logistic regression and defining all the R-squared values.

The classification table measures how well a logistic regression model foretells monetary hardship. The results demonstrate a 94.4% success rate in classifying 572 out of 606 instances that did not include distress. The lower accuracy rate of 40.6% was because only 91 out of 224 distress instances were appropriately detected. The model achieves 79.9% of its predictions correct, which is the total accuracy depicted in Table 8, reporting the classification table of logistic regression.

4.4 Linear discriminant analysis

Several studies in the social and psychological sciences have used linear discriminant analysis (LDA) to estimate the probability of assigning individuals to specific groups (Boedeker & Kearns, 2019; Shayan et al., 2015; Sherry, 2006). Linear discriminant analysis, commonly referred to as LDA, is a statistical technique utilized for both classification and dimensionality reduction purposes. It operates by finding the linear combination of features that most optimally separates two or more data classes from one another. The overarching aim is to maximize the ratio of between-class variance against within-class variance, ensuring that the classes are distinguished from one another as clearly as feasible.

LDA presumes that different classes generate data predicated on dissimilar Gaussian circulations that contain identical covariance matrices. It involves tallying the averages and variances of these distributions and exploiting them to pinpoint the linear discriminants. These discriminants can then be applied to project the data into a lower-dimensional space, simplifying the classification problem immensely.

However, LDA also has limitations. It can struggle with nonlinear boundaries distinguishing classes, and its performance can degrade if the presumption of identical covariance matrices is contravened. Despite these constraints, LDA remains a powerful and popular tool for supervised learning and data examination. As this study is also comparative, we see the standardized canonical discriminant function coefficient indicated in Table 9, which shows that the quick ratio (LN_QR) has the highest explanatory power with a coefficient of 0.897 followed by net profit before tax with 0.408, future cash flow (LN_FCF) with 0.317 respectively. Finally, cash flow from operating activities (LOG_CFO) has least explanatory power with a coefficient of 0.304 for this result. The ability of the discriminant function to distinguish between categories is measured by Wilks' lambda, among other things. The groups may be considered separate since the discriminant function is statistically significant (Wilks' lambda = 0.818, sig = 0.000) as mentioned in Table 9, which reports the standardized canonical discriminant function coefficients. Due to five predictor variables, the degrees of freedom (DF) are five. The efficacy of the discriminant function in differentiating between groups is shown by an eigenvalue of 0.222, which indicates that a considerable share of variance is captured. This value should range from 0 to 1, and our findings met that requirement.

As per the classification findings, the discriminant analysis model successfully categorized 71.1% of the initial grouped instances and 71.0% of the cross-validated cases as mentioned in Table 10, which reports the classification results of discriminant analysis.

Table 9. *Canonical discriminant function.*

LN_QR	0.897
LN_FCF	0.317
NWC	0.033
NPBT	0.408
LOG_CFO	-0.304

Table 10. *Classification matrix for LDA.*

Classification results					
		Financial distress	**Predicted group membership**		**Total**
			Non-distress	Distress	
Original	**Count**	**Non-distress**	446	160	606
		Distress	80	144	224
		Ungrouped cases	76	14	90
	%	**Non-distress**	73.6	26.4	100
		Distress	35.7	64.3	100
		Ungrouped cases	84.4	15.6	100
Cross-validated	**Count**	**Non-distress**	446	160	606
		Distress	81	143	224
	%	**Non-distress**	73.6	26.4	100
		Distress	36.2	63.8	100

Notes: Wilks' lambda: 0.818; Sig: 0.000; DF: 5; Eigenvalue: 0.222

a. 71.1% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 71.0% of cross-validated grouped cases correctly classified.

Accurate case identification for the original dataset was 64.3% for distress and 73.6% for non-distress cases. These percentages stood at 73.6% and 63.8% in cross-validation, respectively. In the first study, the model incorrectly identified 35.7% of distress instances and 26.4% of non-distress cases. For ungrouped instances, the accuracy was more remarkable for non-distress cases (84.4%) compared to distress cases (15.6%). The model is trustworthy since the findings of the original and cross-validated classifications are consistent.

4.5 Artificial neural networks

The data should be normalized since ANN models are nonlinear and do not have constant equations (Teo et al., 2015). Neural network models are popular because they are easy to use, highly predictive, describe both linear and nonlinear systems and do not need assumptions. In order to conduct the ANN analysis, IBM's SPSS neural network module, version 26, was used. For the input and hidden layers, we used multilayer perceptrons with sigmoid activation functions (Sharma & Sharma, 2019). The prediction accuracy may be further enhanced and the number of mistakes reduced by iterative learning (Idrissi et al., 2019). Like Hosamani et al. (2020), we split the samples in two and utilized 70% for training and the rest for testing.

Table 11. *Model summary of ANN.*

Training	**Cross entropy error**	226.814
	Percent incorrect predictions	17.4%
	Stopping rule used	1 consecutive step with no decrease in error
	Training time	0:00:00.05
Testing	**Cross entropy error**	106.361
	Percent incorrect predictions	17.3%

A summary of the model training results shows 226.814 as the cross-entropy error and 17.4% as the percentage of incorrect predictions on the training set; training terminates after one consecutive step without reducing error. Only 0.05 seconds were required for training. On the testing set, the model attained a cross-entropy error of 106.361 and 17.3% of incorrect predictions as mentioned in Table 11, which reports the ANN model summary.

Table 12. *Classification matrix for ANN.*

Sample	**Observed**	**Predicted**		
		Non-distress	**Distress**	**Percent correct**
Training	**Non-distress**	393	17	95.90%
	Distress	82	78	48.80%
	Overall percent	83.30%	16.70%	82.60%
Testing	**Non-distress**	185	11	94.40%
	Distress	34	30	46.90%
	Overall percent	84.20%	15.80%	82.70%

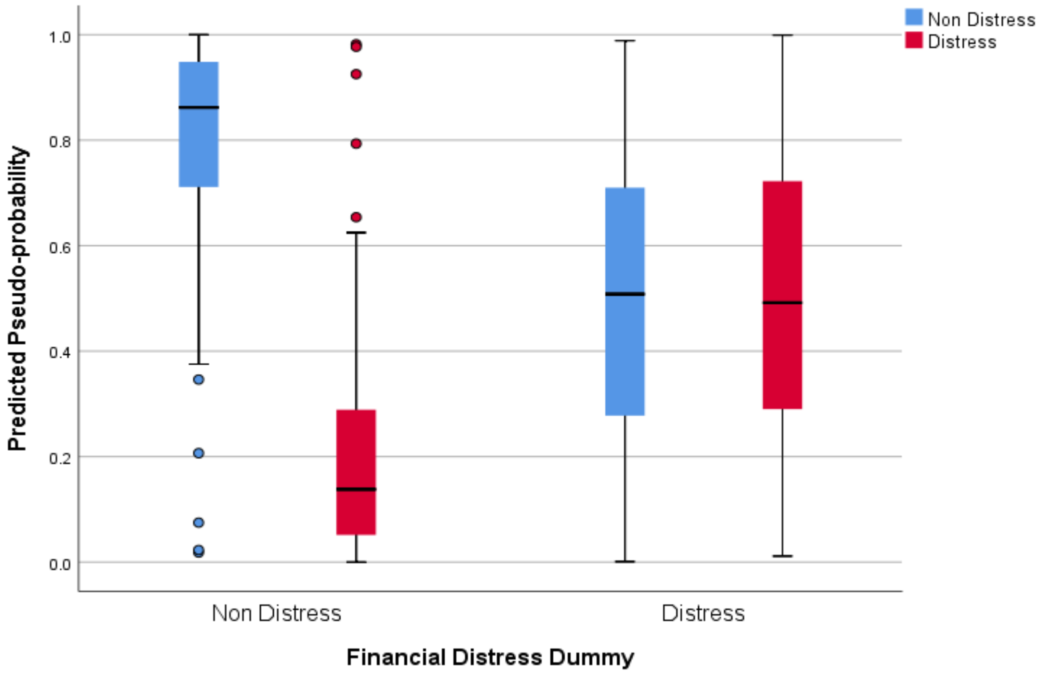

Figure 3. *Pseudo-probability graph.*

The model performance was consistent across both the training and testing sets, indicating its generalizability. When no more progress was seen during training, the stopping rule halted the process to avoid overfitting. As we can see in Figure 3, it indicates the predicted pseudo-probability graph in an artificial neural network (ANN) context. The blue line, which is non-distress, represents the predicted probability that an instance is classified as non-distress and the red line indicates distress, which represents the predicted probability that an instance is classified as distressed. The blue line is above the red line, which means that the model predicts non-distress for that instance. The blue line is above 0.5 and the red line is below 0.5; overall, this implies that the model predicts more percentage probability for non-distress firms and less for distressed firms. On the other hand, it indicates that many firms in the service sector are non-distressed firms and fewer firms are distressed.

The categorization results demonstrate that the model prediction of non-distress is much more accurate than that of distress. Table 12 reports the classification results of ANN. Our analysis was based on 830 company-year data collected over nine years. The model achieved an overall accuracy of 82.60% in the training set, correctly classifying 95.90% of the non-distress samples but only 48.80% of the distress data. As in the training set, the model got non-distress correct 94.40% of the time and distress correct at 46.90%, for an overall accuracy of 82.70%. The artificial neural network (ANN) analysis architecture is depicted in Figure 8.

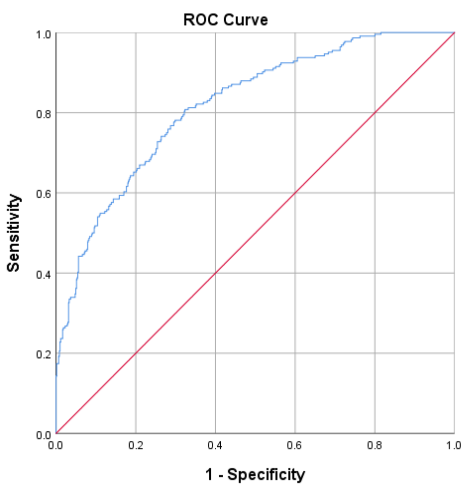

Figure 4. *LR ROC curve.*

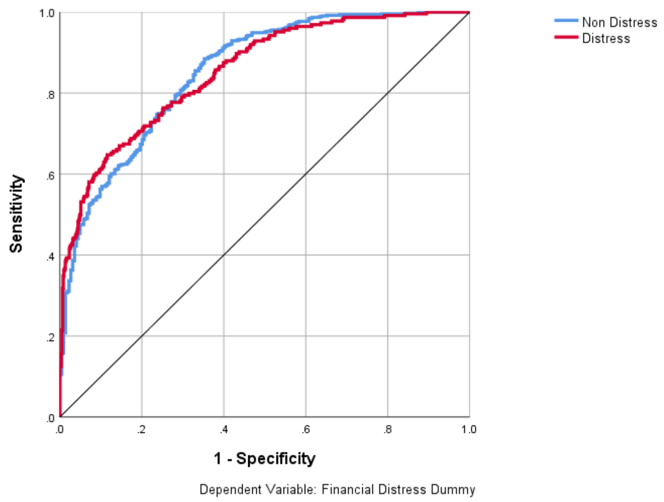

Figure 5. *ANN ROC curve.*

Additionally, we used a ten-fold cross-validating approach to get the RMSE and eliminate the possibility of overfitting (Ooi & Tan, 2016). The average RMSE values of the training and testing procedures are comparatively modest, at 0.639 and 0.638, respectively, as illustrated in Table 13 and diagrammatically represented in Figure 7. Consequently, we can verify that the model fits well, supported by past literature (Flannery & Hankins, 2013). To properly evaluate the predictive capabilities of each input neuron, we conducted a sensitivity analysis (Table 14) to determine the normalized importance of these neurons by splitting its comparative significance among the maximum importance and displaying it as a percentage. The results demonstrate that net profit before tax is the foremost anticipated element, followed closely by perceived net working capital at a normalized importance of 64%. Quick ratio followed at 27% importance, while cash flow from operating activities came in at 18.0%. Based on our investigation, future cash flow displayed the lowest significance at 13%. Table 14 reports the sensitivity analysis.

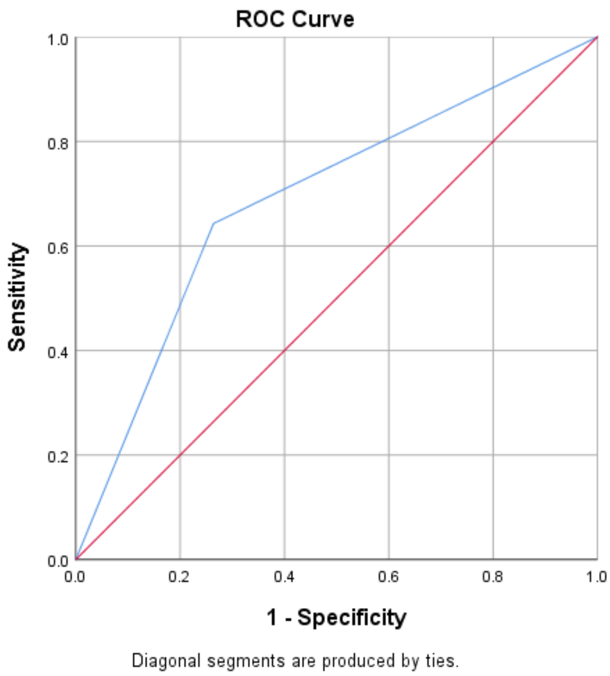

Figure 6. *LDA ROC curve.*

Table 13. *RMSE table.*

Network	Sum of square error (training)	Sum of square (testing)	RMSE (training)	RMSE (testing)	RMSE (training) - RMSE (testing)
1	226.814	106.361	0.631	0.640	0.009
2	224.848	99.816	0.622	0.633	0.011
3	224.91	115.857	0.633	0.656	0.023
4	263.840	91.722	0.676	0.602	0.074
5	221.943	122.784	0.624	0.687	0.063
6	243.749	91.563	0.644	0.614	0.031
7	231.794	109.568	0.634	0.658	0.024
8	241.69	94.418	0.643	0.621	0.022
9	242.832	106.634	0.642	0.667	0.025
10	238.783	88.629	0.638	0.604	0.034
Mean	236.120	102.735	0.639	0.638	0.001
Std. dev.	12.775	11.411	0.015	0.027	

Table 14. *Sensitivity analysis.*

Variables	NI 1	NI 2	NI 3	NI 4	NI 5	NI 6	NI 7	NI 8	NI 9	NI 10	AVG	NI (%)
LN_QR	0.290	0.161	0.252	0.445	0.338	0.173	0.352	0.240	0.306	0.186	0.274	27%
LN_FCF	0.127	0.116	0.097	0.186	0.089	0.084	0.163	0.131	0.205	0.112	0.131	13%
NWC	0.594	0.916	0.915	0.544	0.480	0.653	0.380	0.759	0.485	0.695	0.642	64%
NPBT	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	100%
LOG_CFO	0.184	0.135	0.146	0.130	0.200	0.144	0.237	0.198	0.251	0.160	0.178	18%

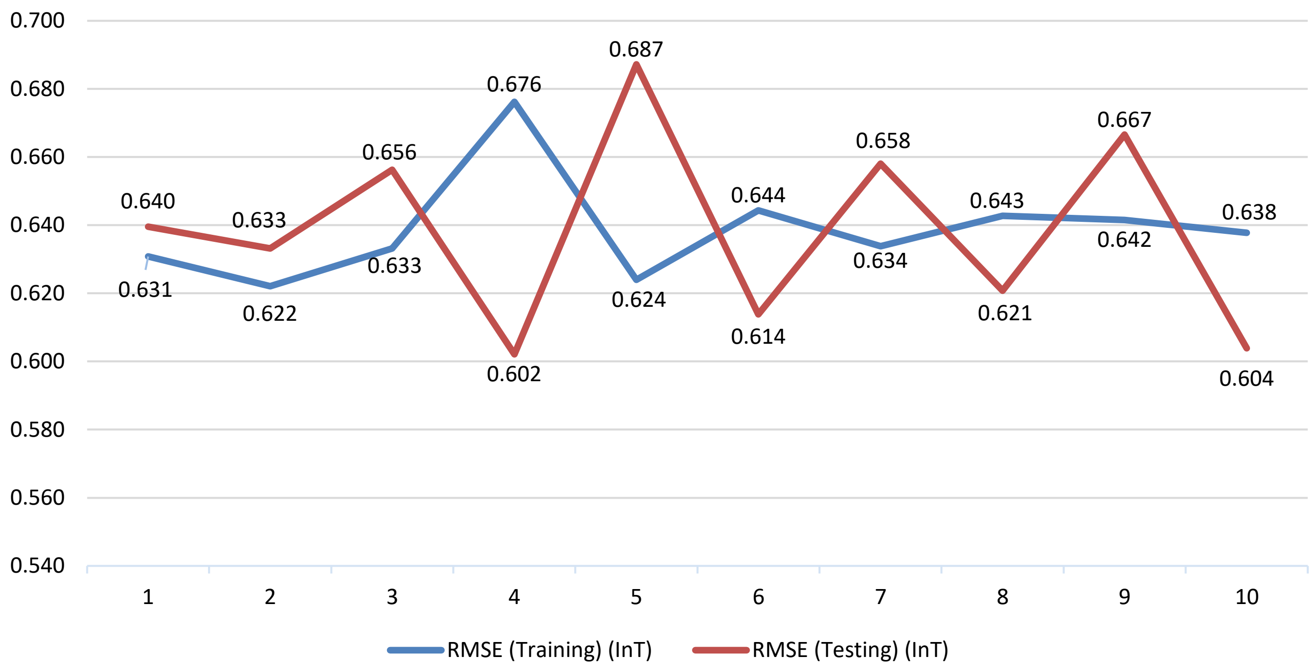

Figure 7. *Graphical representation of RMSE chart.*

4.6 Model comparison

Several indicators are employed to measure model performance to provide a complete picture of how well predictive models work. Table 15 reports the different parameters for the measurement of model performance and accuracy. Overall accuracy is the percentage of cases accurately predicted relative to the total instances. Both sensitivity (or recall) and specificity (or actual negative rate) measure how well a model can detect false positives and negatives, respectively. Predictions that turn out to be correct are measured by precision.

Table 15. *List of model comparison parameters.*

Performance measures	
Metric	Formula
Accuracy	TP+TN/(TP+FP+FN+TN)
Sensitivity or recall	TP/(TP+FN)
Specificity	TN/(FP+TN)
Precision	TP/(TP+FP)
F1 Score	2 × Precision × Recall / (Precision + Recall)
MCC	$\mathrm{TP} \times \mathrm{TN} - \mathrm{FP} \times \mathrm{FN} / \sqrt{(TP + FP)\ (TP + FN)\ (TN + FP)\ (TN + FN)}$
AUROC	Sensitivity versus specificity plot

Notes: MCC: Matthews correlation coefficient. AUROC: Area under the receiver operating characteristics curve.

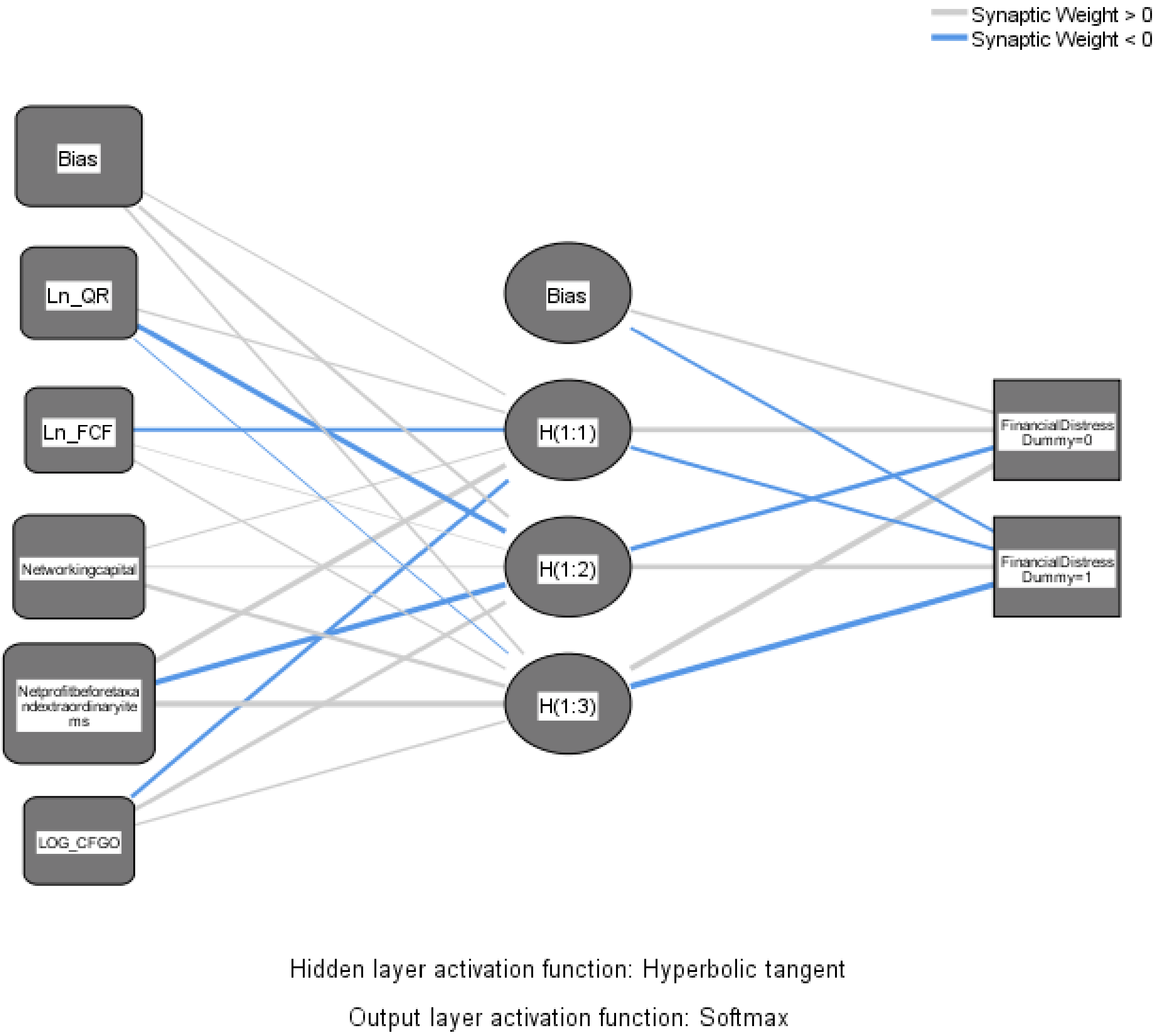

Figure 8. *Hidden layer activation function.*

On the other hand, the area under the receiver operating characteristic curve (AUROC) visually demonstrates the class discrimination capabilities and accuracy of a model. By finding the harmonic mean of recall and accuracy, the F1 score provides a single measure of performance that is both balanced and comprehensive. Finally, even with unbalanced datasets, the Matthews correlation coefficient (MCC) provides a balanced metric by including both true and false positives and negatives. An β1 coefficient indicates a faultless forecast, while a -1 coefficient indicates complete disagreement between the estimates and actual values.

A zero coefficient suggests that the prediction is no better than chance (Powers, 2011; Boughorbel et al., 2017). Together, these measures give overall a good idea of how accurate and robust a model is. A few companies need to improve their financial position, as shown by the findings of the individual models because a percentage of firms are in distress in the Indian non-financial service sector. We find that the ANN model outperforms the others by comparing the prediction accuracy of the three models. It has the lowest error value, incorporates the most variables and achieves a higher accuracy percentage of around 82.63% in training and 82.69% in testing. In the original and cross-validation scenarios, LR achieves value predictions that are approximately 80% overall accuracy, whereas LDA maintains a minimum of 71.08%. While this result does not provide an accurate forecast of bankruptcy status, it does indicate a greater likelihood of bankruptcy due to financial distress. It is not only about overall accuracy, as we can see in Figure 9 and Table 16; it is clearly depicted that in overall parameters, the artificial neural network is at the top of most parameters and LR takes second place from this point of view. Table 16 reports the performance comparison between LR, LDA and ANN. Looking at the ROC curve, which is also closest to 1 in the ANN model (Figure 5) compared to the two other models, i.e., LR (Figure 4) and LDA (Figure 6), which also indicates the good accuracy (Wang et al., 2021). Our results are also supported with a past study (Mishra et al., 2021). Our research directly opposes the work of Altman et al. (1994), which indicated that LDA outperformed ANN by a minor margin.

Table 16. *Model performance analysis. Performance comparison between LR, LDA and ANN.*

	Overall accuracy	Sensitivity	Specificity	Precision	F1 score	MCC	AUROC
LR	79.87	40.6	94.38	72.8	52.12	43.45	81.8
LDA							68.9
Original	71.08	64.28	73.59	47.36	54.53	34.9	
Cross validation	70.96	63.83	73.53	47.19	54.26	34.51	
ANN							85.3
Training	82.63	48.75	95.85	82.1	61.17	53.77	
Testing	82.69	88.23	94.38	73.17	79.99	48.77	

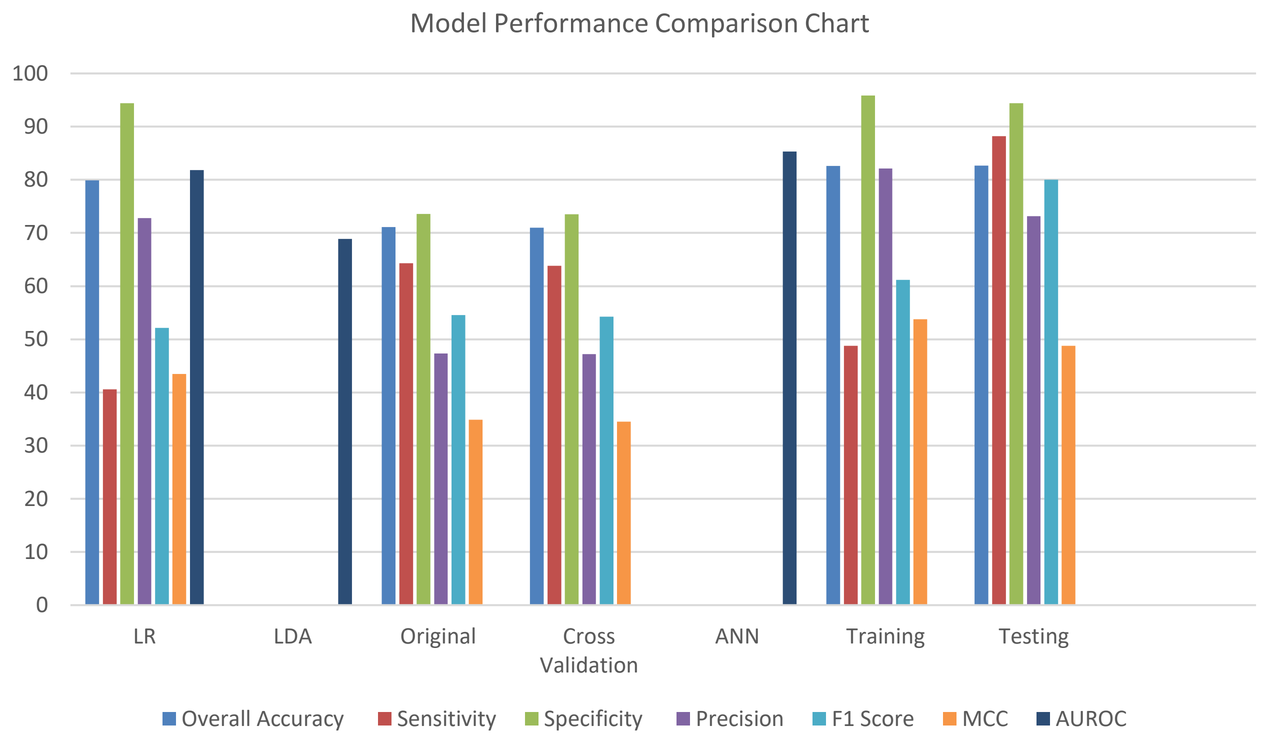

Figure 9. *Model performance comparison chart.*

5 DISCUSSION

The study found that all the variables—quick ratio, future cash flow, net working capital and net profit before tax—have an inverse relationship with the dependent variable at less than 0.05 level of significance, while cash flow from operating activities appears insignificant. On the other hand, the classification model performance analysis showed that the ANN model has a higher accuracy and area under the receiver operating characteristic curve than the LR and LDA models. Specifically, the tests yielded an accuracy of 82.69% with a sensitivity of 88.23% and an AUROC of 85.3, indicating good predictive performance regarding the primary attribute. It showed lower sensitivity at 40.6% and higher specificity at 94.38%, revealing the inherent conservatism of LR in identifying financial distress. LDA displayed a fair performance in terms of AUROC, with 68.9. These findings indicate that the ANN model performs better with the service sector firm data distinguishing financial distress. In addition, from sensitivity analysis, we found that NPBT was the most important predictor demonstrating robust profitability.

The paper on predicting financial distress addresses a vital research agenda to inform public policy by determining early warning signals for financial frailty. Through financial ratio analysis, we show the model effectiveness in capturing the dynamics of distress within the sectors, providing insight into the design of policy responses. Ultimately, the study contributes to informed policymaking that promotes economic stability, sustainability and the well-being of communities, aligning with broader societal goals and development objectives.

6 CONCLUSION

For the years 2012/2013 to 2020/2021, we used three distinct methodologies—linear discriminant analysis, logistic regression and artificial neural networks (ANN)—to examine instances of business difficulty and insolvency involving non-financial sector enterprises in India. All the approaches relied on financial ratios, particularly those anticipating future cash flow and accounting indicators, which are essential in determining bankruptcy status. The accuracy of the forecast determines which of the three models employed in this prediction is utilized. Predicting bankruptcies on the underlying sample yielded the best results when using ANN, which reached an accuracy of 88.9%. LDA had a respectable but low prediction accuracy score of 70.96% in cross-validated instances and 71.08% in the original ones. By estimating India's best bankruptcy prediction model, this research reveals which companies went bankrupt between 2012 and 2021. It demonstrates that some companies showed symptoms of financial distress due to poor performance.

The study findings suggest that future cash flow has a substantial effect on financial distress prediction, an essential new variable that needs to be considered in future research. A better indicator of possible liquidity problems and operational effectiveness than historical data, future cash flow gives a view into a company's financial health that is looking forward. This new understanding improves the forecasting capability of models for financial hardship by allowing more precise risk assessment and proactive management tactics. Decisions made by companies and investors with an eye on the future cash flow may help reduce the likelihood of bankruptcy and boost financial security. On the other hand, all the other variables except cash flow from operating activities, i.e., quick ratio, net profit before tax and net working capital, significantly affect the prediction of financial distress, which indicates their important role in forecasting bankruptcy. From the sensitivity analysis, we found that net profit before tax is the most important predictor among them, which also depicts its importance for predicting financial distress.

6.1 Policy implications

Our research offers insights into public policy design by contrasting predictive analytics approaches to forecasting future cash flows. Regulators can utilize precise early distress warnings to establish support programmes and governance, fostering stability. In order to keep the company's finances in good shape, it is recommended that Indian regulatory authorities keep an eye on the important financial indicators found in this study. The artificial neural network (ANN) model developed in this study also serves as a useful tool for evaluating challenging financial situations and opens up a lot of possibilities for future research into distress forecasting in the Indian corporate sector.

According to our results, based on its efficacy in handling complicated datasets and freedom from the constraints of linearity and normalcy, ANN is the best prediction model for more extensive financial datasets, which means that it is the most excellent technique for forecasting company failures. This work highlights the superiority of nonlinear pattern learning models over linear ones in predicting financial soundness. It introduces a new category of computational tools that analysts with a tech background and credit issuers may use. To alert the business sector, this research creates and finds an effective model for predicting financial problems. Companies can manage risk better if our findings help them anticipate financial instability.

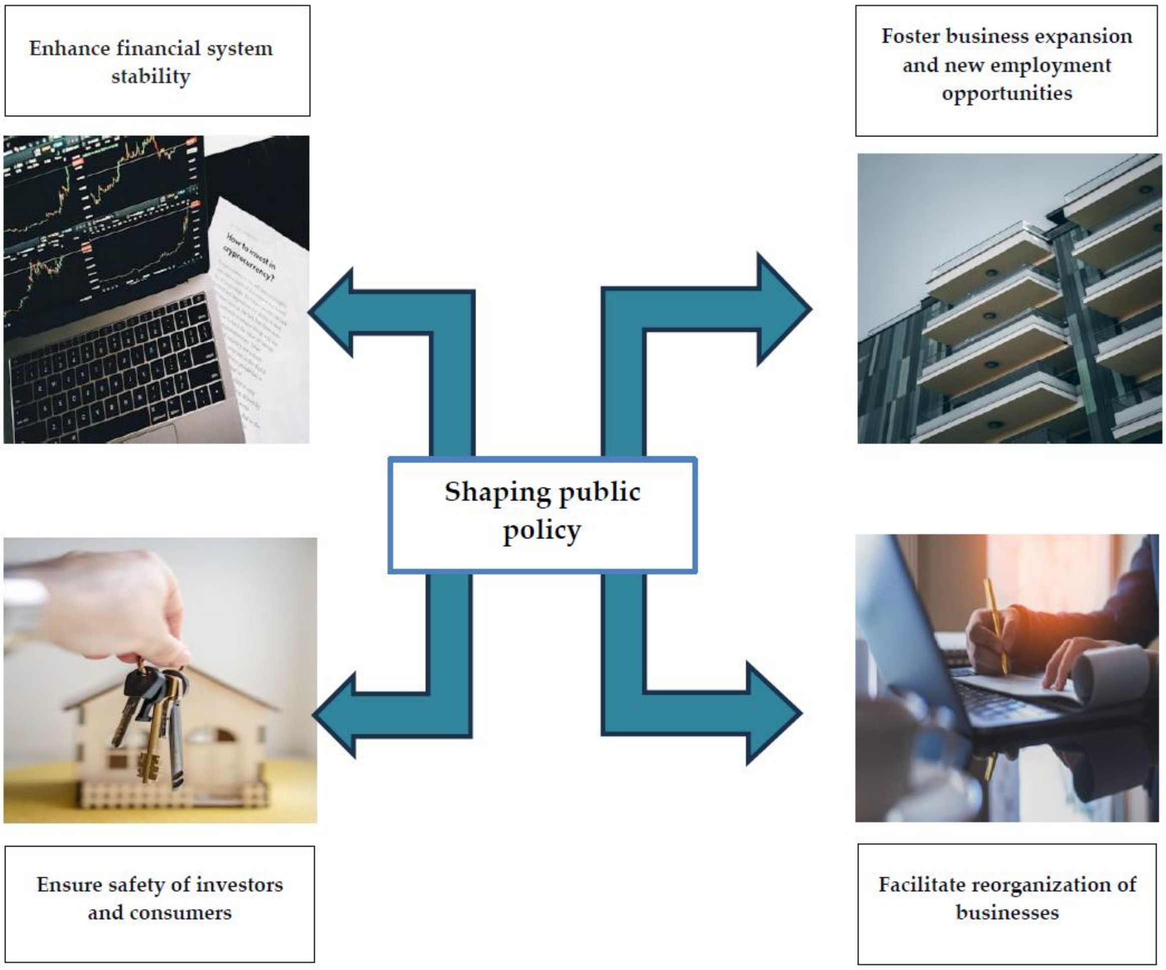

Figure 10. *Shaping public policy. Compiled by authors from freely available images on https://www.pexels.com.*

6.2 Implications for public policy

The study's methods for evaluating a company's financial health and predicting possible financial problems make it very valuable for public policy, as depicted in Figure 10. Policymakers may utilize these data for the following purposes.

6.2.1 Enhance financial system stability

An early warning system, where they can take precautions by identifying businesses that could be in financial trouble. Some possible solutions include establishing early intervention programmes to assist failing businesses, urging banks to engage in responsible lending practices or imposing stricter rules on high-risk sectors. A financial crisis may have a domino effect for the whole system if not addressed quickly (Mahadik & Mohanty, 2024). As a result of our findings, lawmakers will be better equipped to craft legislation that promotes the effective distribution of capital. Better financial crisis prediction technologies allow investors to channel their capital into financially stable enterprises with promising future cash flow. Both the expansion and stability of the economy are bolstered by this.

6.2.2 Ensure safety of investors and consumers

- **Consumer protection:** If investors rely on better crisis prediction tools, they could put their money into businesses that are more likely to be financially secure and have a good chance of making a profit in the future. This is a boon to the economy's growth and stability.
- **Investor protection:** Investment protection rules could be shaped by the findings of this study. If financial distress risks were openly reported, investors would have more information to make informed decisions and avoid risky ventures. If investors suffer financial losses due to fraud, the government may institute programmes to compensate them.

6.2.3 Foster business expansion and new employment opportunities

- **Focused assistance:** Government authorities may set up targeted aid programmes by identifying which companies have the most significant potential for future cash flow. Tax incentives, loan guarantees and preferential resource access might be available to promising businesses. Putting money into successful companies boosts the economy and generates employment opportunities.
- **Market efficacy:** Consumers stand to gain from a more efficient market if we can improve our ability to predict when they may have financial difficulties. The market becomes a more secure investment location when hazardous companies are removed. Inspiring initiative and fresh ideas foster a perfect environment for flourishing firms.

6.2.4 Facilitate reorganization of businesses

- **Early intervention:** Businesses have a better chance of resolving financial issues before they spiral out of control if they can identify them early on. This aids in the successful reorganization of businesses. New financing sources, debt settlement negotiations or programme reorganization may be required. Prompt action might prevent costly bankruptcies, preserve shareholder value and save jobs.
- **Better bankruptcy procedures:** Legislators may find our conclusions helpful in pursuing more efficient bankruptcy processes. By estimating the potential of distressed organizations, lawmakers may design bankruptcy rules that prioritize reforming and saving firms wherever possible.

6.3 Limitations and future research directions

Analysts may discover opportunities for improvement in the neural networks after using the approach to forecast bankruptcy, which may provide greater foresight. Improved training techniques and feedback might help them. A more efficient input produces a better forecast. Potentially distinct but related financial indicators may be used in future research to examine insolvency. While we have focused on the study's potential influence on public policy, other scholars may choose to investigate the effects of sustainable organizations on insolvency from a social and environmental perspective. Is there a connection between the capacity to forecast financial crises and sustainability? Does this influence the model efficiency, which aids in sustainability? It is possible to include additional indicators in all of the methods used in this research, including LR, LDA and ANN. A little more adequateness in the data selection procedure is possible. There is a need for more data from most firms and a small set of indicators defined by these companies. To make a more thorough investigation, it is possible to track down and gather those data, revealing hitherto unknown tendencies among the affected businesses. Future research might improve upon the models predicted in this study by including more accounting data and factors. For more accurate findings, researchers may break down the market by industry and develop prediction models tailored to each. They can also make case studies to investigate the real impact. For the best forecast of Indian enterprises' bankruptcy, one may test, use and pick models such as mixed complex models, genetic algorithm NNs, decision tree models, AMOS, GB, XGB and probit analysis.

ADDITIONAL INFORMATION AND DECLARATIONS

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