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A review on the techniques adapted for the prediction of financial distress in Indian Steel companies

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Abstract:

In India, steel industry is considered as one of main industries because of its backward and forwards connection with other sectors namely building, transportation and more. Successes of any organization rely on its potential for managing its finances efficiently. Finance is seen as most viral part in the organization. If economic performance and health is affected in the company than it affects its growth, development, sustainability, and thus effective management of economic resources is needed and need proper attention for optimizing the financial resources. Predicting financial insolvency or distress in any company assists groups within the firms such as employees, financiers, stakeholders, customers, contractors for taking appropriate decision. Therefore, this research reviews methods or techniques for predicting financial distress in steel companies with specific reference to India. The techniques namely Altman Z score model, survival analysis, logistic regression, neural network and data envelopment analysis have been identified to be the major techniques adapted by organizations. The research also provides strategies on how this research could be extended in the future.

Keywords: Financial distress, Altman Z score model, logistic regression, neural network, data envelopment analysis and survival analysis

1. Introduction:

India is one of emerging economies in the world. Economic growth is contributed by many sectors in India. Steel industry was seen as backbone of Indian economy. Consumption of steel per capita in all nations is seen as main aspect for measuring growth and livelihood of socio-economical factor (Kogila and Vasanthi, 2019). Pradhan (2021) stated that India is 2nd highest manufacturer of steel in the globe. Many steel businesses are present in Indian industry. Steel provide raw materials with other sectors and give workers with indirect and direct work opportunities (Kogila and Vasanthi, 2019). For economy and people, expansion of steel Industry in India is important. Each firm success is based on the financial growth and Financial are fundamental for commercial activity that are predicted by its efficient performance of finance.

It is important for each firm owner to estimate the economical health of their firm as easily and quickly as possible. It is vital to identify, whether firm could maximize its value and give an assurance that investment in firm would get a return. Further, it always questionable that how does financial health of firm are predicted and estimated. It is significant to monitor economical performance of firm. Many approaches are there for measuring the financial health of the firm and forecast its bankruptcy and financial distress and rely on present situation of the market, as there is change in growth of such measures adopted for prediction of financial health (Mokrisova and Horvathova, 2020).

Tian and Yu (2017) pointed out that financial health could be improved by determining organization are at understanding risk in economical distress in future. Such before warning help some organization to take suitable modifications for avoiding future bankruptcy and financial distress, such prior measures or warning could help in reducing the costs of business failure and financial distress, for example

- Investors exactly manage the risk data of their assets and enhance their performance by not spending in future failures
- Stakeholders like customers and suppliers would give best data for making long-term decisions
- Institutions from finance could manage their exposure and amount of bad debts in future

Exact before warnings would give financial stability and minimize costly infectious impacts same to those noticed with financial crisis at global level when industry failing outcomes in another industry failing and more. Prediction of financial distress also referred as prediction of firm or business failure and prediction of bankruptcy includes emerging approaches of data mining and statistical models on the basis of publicly presented data like financial ratios which give such before warnings (Gupta and Gopalkrishan, 2019)

There are various researchers and scholars adopted statistical methods (Giannopoulos and Sigbjornsen 2019, Ho et al, 2013 Alaka et al. 2018, Delen et al. 2013 and Barboza et al. 2017) for predicting bankruptcy and they face some difficulties with statistical technique like independence, normality and linearity among variables (Jayasekera 2018, Tian and Yu 2017 and Altman 2018). In recent days, researchers have changed to intelligent methods from statistical methods like vector support machines, genetic algorithm, fuzzy logic and neural network (Callejon et al. 2013, Tsai 2014, Dong et al. 2018, Acosta-González and Fernández-Rodríguez 2014, Sun et al. 2014, Jardin 2015, Succurro et al. 2019, Garcia et al. 2019, Jardin 2018 and Hosaka, 2019).

Gordini (2014) adopted genetic algorithm for predicting financial distress and achieved 84.4 percent overall predictive performances. Zelenkov et al, 2017 also adopted genetic algorithm and 93.4 percent accuracy was noticed with prediction. Further Barboza et al (2017) compared eight models for prediction. Here, models of machine learning were compared with statistical ones. Models included in this research are support vector machines (radial and linear basis), logistic regression, random forest, discriminant analysis (Altman Z-score), boosting, artificial neural networks and bagging. From the findings of the research, it was noticed that highest accuracy rate in prediction was identified and also outperformed well by boosting, bagging as well as random forest models when compared with other models. Ansari et al (2020) adopted particle swarm optimization, magnetic optimization algorithm and artificial neural network (ANN) hybrid model and model accuracy was found to be 99.7 per cent.

Huang and Yen (2019) mentioned that all such methods have their own positives and negatives. Based on data, few methods provide highest accuracy than others. In addition to that, authors also adopted data envelopment analysis (Gupta, 2017) and survival analysis (Lee, 2014) for predicting financial distress in the companies. Model of random forest with adoption of Altman variables was found to be 95 per cent performance and outperforms when compared with other models (Linear Discriminant analysis, Altman Z score, Quadratic discriminant analysis). Random forest method has indicated high performance for privately traded firms when compared with publicly traded companies (Cindik and Armutlulu, 2021).

2. Literature Review:

Predicting techniques taken into consideration in this research for finding financial distress in steel companies with specific reference to India are Altman Z score technique, neural network, survival analysis, data envelopment analysis and logistic regression.

2.1 Altman Z score technique

It was mentioned by Chavali and Karthika (2012), Edward Altman expanded a famous model for predicting bankruptcy namely Altman Z score model. It is also known as MDA (multiple discriminant analysis). Gupta and Gopalkrishan (2019) adopted Altman Z score model for identifying financial distress. Two firms were in safer side from ten firms. At the same time, it was also revealed that steel industry financially performed well in spite of impact of global slowdown and low demand throughout the period of research. Apoorva et al (2019) pointed out Altman Z score is nearly 85 per cent useful and accurate prediction. Further Gnyana, 2015 suggested that firms often have to calculate Z-score to improve the financial health. Altman Z-score helps to identify danger and weaker zones in companies (Saini, 2018).

A research was carried out by Kashyap and Bansal (2019) for constructing a statistical model with the help of accounting ratios for forecasting financial distress from listed firms in India. This research selected companies which registered with bankruptcy code and new insolvency. MDA was adopted for discriminating the firm between healthy companies and financial distressed firms. From the outcomes of the study, financial ratios are helpful to discriminate between non-distress and distress companies. Outcome identify that financial ratio could accurately forecast bankruptcy among firms in India prior two or three years. It was clear that MDA are adopted for finding out firms which face distress in advance or in future.

Chaudhery and Patel (2021) assessed financial health by adopting Altman Z score model and for predicting the opportunity of bankruptcy for chosen steel companies with specific reference to India. It was found that SAIL, Tata Steel BSL and Jindal Steel's financial health was weaker and in distress area throughout the research time. It was suggested that these firms management have to take appropriate measures for improving their condition in finance or there will be high risk of distress in future.

Anuj et al (2018) revealed the risky position of steel companies especially in India. This research studied about big and small companies which face insolvency and crunch in India. High expenditure of capital, outdated technology and excessive inputs are the major cause for financial distress. This research indicated no working capital for most of firms. Steel industry is one of superior number of defaulters in code of bankruptcy. In general, health of steel industry is weaker. Thus, this study indicates Altman Z score for measuring the future bankruptcy and distress of the firm and act as competitive tool. In addition to that, Altman Z score application discloses true condition of firms and provides a glance of default areas for every firm. At the same time, Altman Z score method has some qualitative factors linked with and also has impact of fiscal health of firm (Gopalakrishnan et al, 2019).

Interestingly Gugnani (2020) claimed that Altman Z score act as a prediction method, further it is chance from firm's financials, and it seems like financial distress happens as well as management also achieve in enhancing matters. It is sensible for investor for keeping an eye on solvency of the firm. Poorest zone based on economical health is considered as distress zone where firm has high chance of going insolvent. This does not refer if a firm is distress area has a chance for insolvency rather management can play a vital part in deciding the fate of firm and all recognition goes to management for success. It was also observed that TATA steel was successful to change in its identified zone that is firm's management take effective decisions that assisted the firm to enhance.

Chandra and Selvaraj (2013) recommended that all chosen steel firms have to put more efforts for increasing Z-score. This would assist them in avoiding any harm to its solvency and liquidity position, thus avoid financial distress and enhance the entire fiscal health. Gunathilake (2014) mentioned that Springate's and Altman's Z score models have same ability in prediction. Altman Z score model has superior power in identifying distressed companies prior 1 year. Likewise Mahalakshmi (2015) pointed out Altman's model could forecast distress for at least 4 years prior insolvency. Further it was identified by Rathnayake and Samarakoon (2020) that Altman's model could forecast insolvency within 1 year prior with 72.10 percent accuracy rate.

S.No.	Author	Year	Model used	Contribution
1	Gupta and Gopalkrishan	2019	Altman Z score	Steel industry financially performed well in spite of impact of global slowdown and low demand throughout the period of research
2	Gnyana	2015	Altman Z score	Firms often have to calculate Z-score to improve the financial health
3	Kashyap and Bansal	2019	Altman Z score	MDA are adopted for finding out firms which face distress in advance or in future
4	Chaudhery and Patel	2021	Altman Z score	Firms management have to take appropriate measures for improving their condition in finance or there will be high risk of distress in future
5	Anuj et al	2018	Altman Z score	Altman Z score application discloses true condition of firms and provides a glance of default areas for every firm
6	Gugnani	2020	Altman Z score	Poorest zone based on economical health is considered as distress zone where firm has high chance of going insolvent
7	Chandra and Selvaraj	2013	Altman Z score	Adopted model assist them in avoiding any harm to its solvency and liquidity position, thus avoid financial distress and enhance the entire fiscal health

Figure 1: Altman Z score model in predicting financial distress

Source: Author

2.2 Neural Networks:

Horváthová et al (2021) applied two models namely feed-forward NN (neural network) and MDA. NN is appropriate substitute to assess financial health. It was verified that high indebtedness was predicted during bankruptcy. Performance for predicting ANN outperformed well than other alternative models in four metrics namely specificity, precision, accuracy and sensitivity. Artificial NN (ANN) conducts weighting techniques for producing best result on each layer. Predictor opportunity is important on predictive method and could be identified with statistics (Nur and Panggabean, 2019).

Du Jardin and Severin (2012) carried out an investigation to determine the accuracy rate in predicting financial distress in companies with neural networks and logistic regression. It was found that neural networks could predict distress with 81.3 percent accuracy over one year. At the same time, it was also noticed that logistic regression predicts distress with 81.6 percent accuracy over one year. At the same time Tutien (2021) and Kim et al (2018) pointed out that neural network could predict insolvency in the companies in an effective way. Further Kim et al (2018) added that NN in hidden layer with forty two nodes determined accuracy of 71.9 percent chosen from 1548 heavy industry firms with 41 financial ratios in Korea. For predicting insolvency in Greek industry, neural networks were adopted. It was found that NN had good rate for classification of about 65.7 percent prior two years of insolvency and 70 percent prior one year of insolvency (Papana and Spyridou, 2020). In addition to that, Paule-Vianez et al (2020) confirmed that financial distress was predicted with 97.3 percent accuracy with neural networks in credit institutions.

Jan (2021) carried out the research for building effective and high-accuracy financial distress models for prediction with these algorithms namely convolutional NN (CNN) and deep NN (DNN). Further significant variables are chosen by CHAID (chi-squared automatic interaction detector). In this research, OTC and Taiwan's listed sample firms' data are taken into consideration from TEJ (Taiwan Economic Journal) database between 2000 and 2019 encompassing 258 companies not in bankruptcy and 86 firms n bankruptcy. From the empirical outcomes, associated with significant variables chosen by CHAID as well as modeling by convolutional NN, CHAID-convolutional NN model had predicted financial distress with 94.23 percent accuracy and lowest type II and type I error rate that are 4.81 and 0.96 percent respectively.

Koral (2019) adopted prediction models using various methods such as decision trees, multilayer artificial NN, fuzzy sets and recurrent NN. From the outcomes of the study, it was observed that 2nd best predicting model is recurrent NN model with accuracy rate 91.2 percent prior 3 year of financial crisis. It was also noted that nearly 95.2 percent accurate classifications at least 1 year before insolvency. After examining the dynamic models effectiveness and it was noticed that fuzzy sets, decision tress, multi layer artificial NN and recurrent NN perform well in terms of prediction rate prior 6 years of insolvency with accuracy rate above 80 percent. Further Vochozka et al (2016) and Vochozka et al (2015b) also proposed models to predict insolvency of Czech construction and manufacturing firms with help of artificial NN with effectiveness of 90 percent.

S.No.	Author	Year	Model used	Contribution
1	Horváthová et al	2021	feed-forward NN, MDA	High indebtedness was predicted during bankruptcy
2	Nur and Panggabean	2019	Artificial NN	Predictor opportunity is important on predictive method and could be identified with statistics
3	Du Jardin and Severin	2021	Logistic regression and NN	Neural networks could predict distress with 81.3 percent accuracy over one year
4	Kim et al	2018	Neural network	NN in hidden layer with forty two nodes determined accuracy of 71.9 percent
5	Paule-Vianez et al	2020	Neural network	Financial distress was predicted with 97.3 percent accuracy with neural networks
6	Jan	2021	convolutional NN and deep NN, CHAID-CNN	CHAID-convolutional NN model had predicted financial distress with 94.23 percent accuracy and lowest type II and type I error rate that are 4.81 and 0.96 percent respectively.
7	Koral	2019	Decision trees, multilayer artificial NN, fuzzy sets and recurrent NN	It was noticed that fuzzy sets, decision tress, multi layer artificial NN and recurrent NN perform well in terms of prediction rate prior 6 years of insolvency with accuracy rate above 80 percent

Figure 2: Neural Network in predicting financial distress

Source: Author

2.3 Data Envelopment analysis:

DEA was adopted for classifying companies into categories of healthy and non-healthy (Premachandra et al, 2011, 2009 and Shetty et al, 2012) or computing aggregating effective scores are adopted within prediction frameworks, stochastic or statistic modelling (Xu and Wang, 2009, Yeh et al, 2010, Psillaki et al, 2010, Horvathova and Mokrisova, 2018 and Li et al, 2013). Mousavi et al (2015) adopted DEA as framework for evaluating performance to compete with models of bankruptcy prediction. Stefko et al (2020) studied about methods for predicting insolvency of the firm with intention to choose a prediction method that would provide accurate results. Conventional prediction models in insolvency are appropriate tool to predict economical problem of companies. At the same time, these kinds of tools are mainly adopted for defining economical indicators. Thus DEA method was adopted since it is appropriate substitute to predict the failure of examined sample of companies. When compared with logit model, outcomes of DEA are not dependent of any kind of statement. Using DEA, main success factors for future are identified. Such outcomes could assist firms to enhance their financial competitiveness and health.

DEA is non-parametric method, relatively low and it is one of major probable methods in helping the economical health of companies and insolvency risk when compared with statistical methods (Stefko et al, 2018). However Paradi et al (2014) and Premachandra et al (2011) confirmed that conventional cut-off points (0.5) are inappropriate to assess the estimation accuracy in insolvency models. Cut off point is identified as 0.63 for DEA model (Stefko et al, 2020).

Setiawan and Diana (2020) compared conventional tools for prediction namely Altman's Z score model with novel developed DEA method. It was revealed that prediction of DEA's approach has superior rate in accuracy when compared with conventional tool. Accuracy rate of DEA was found to be 85.71 percent which is higher than Altman Z score model. DEA was found to have best power in prediction when compared with conventional Altman Z score with accuracy test. High rate of accuracy is mostly influenced by major choice of output and input variables. Possibly, output of working capital, that estimate the liquidity and it refers to economical health. It also has high effect in forecasting distress and maximizes the accuracy rate. DEA model found as an effective tool in predicting financial distress. It is novel non-parametric technique than traditional model and generally used to estimate the efficiency in production of manufacturing and efficiency of bank (Condello et al, 2017).

Paidar et al (2021) stated that based on impacts of economical distress on financial institutions, they are forecasted by DEA model with using efficiency of SBM (slacks-based on measure) and unique approach. It was found that 61 percent of the forecasts were accurate with technique of DEA and 39 percent of prediction was inaccurate. Horvathova and Mokrisova (2018a) adopted major models BCC DEA model and modelled with software of DEA frontier and logit model was modelled with statistica software. Estimation accuracy was compared with logit model and DEA model using error type I and type II. It was obvious from the findings of the estimation are DEA method is appropriate substitute to assess the economical health of firm.

S.No.	Author	Year	Model used	Contribution
1	Mousavi et al	2015	DEA	DEA as framework for evaluating performance to compete with models of bankruptcy prediction
2	Stefko et al	2020	DEA and logit model	Using DEA, main success factors for future are identified. Such outcomes could assist firms to enhance their financial competitiveness and health
3	Stefko et al	2018	DEA and statistical methods	It is one of major probable methods in helping the economical health of companies and insolvency risk
4	Setiawan and Diana	2020	DEA and Altman Z score model	DEA was found to have best power in prediction when compared with conventional Altman Z score with accuracy test.
5	Condello et al	2017	DEA	It is novel non-parametric technique than traditional model and generally used to estimate the efficiency in production of manufacturing and efficiency of bank
6	Paidar et al	2021	DEA model with using efficiency of SBM (slacks-based on measure) and unique approach	It was found that 61 percent of the forecasts were accurate with technique of DEA and 39 percent of prediction was inaccurate
7	Horvathova and Mokrisova	2018a	BCC DEA model and logit model	DEA method is appropriate substitute to assess the economical health of firm.

Figure 3: Data envelopment analysis in predicting financial distress

Source: Author

2.4 Logistic Regression:

Verma and Raju (2021) proved that logit model performed well in terms of classification when compared with MDA and such outcomes are similar to findings of Hasan, 2016. Developed LR (logistic regression) model is powerful when compared with MDA which is obvious from Box M's result and HosmerLemeshow test (Raei et al, 2016). Kherrazi and Ahsima (2016) adopted a binomial LR model for identifying the determinants of failure in small and medium sized firms. Outcomes of the model indicated that failure of small sized firms is based on without permanent funds and commercial profitability.

Khlifa (2017) developed a LR model for predicting the risk of selected companies in Morocca. Model gave a classification rate over 2 years with 88.2 percent. It was also found out LR model give better accuracy rate than MDA. Iturriaga and Sanz (2015) acquired 81.73 percent accuracy with LR model before 1 year of insolvency and at the same time 77.8 percent accuracy with MDA before 1 year of insolvency. Further it was added by Affes and Hentati-Kaffel (2019) and Jardin (2015) that LR performs well than MDA in accuracy of prediction.

Hassan et al (2017) pointed out that LR model is very beneficial than Altman Z score model for better forecast in economical bankruptcy. Exact forecast of bankruptcy is helpful in enhancing the regulation of firms, for forming policies for firms and follow any preventive measures if any emergency occur in future. Policy makers also gain from LR tool and it act as a tool to economical system which prevails in markets. At the same time, this could be adopted for analyzing the economical decisions of companies and its risks.

It was suggested by Shrivastava et al (2018) that Bayesian methodology outperforms well in accuracy and model parameters. It also has high ability in prediction than logistic model. Likewise, model was proposed for adopted for predicting the distress on the basis of testing data, Bayesian logistic model was identified to perform well than conventional logistic model. Malakauskas and Lakstutien, 2021, Lukason and Andresson, 2019 and Du Jardin and Severin, 2012 proved that LR model performs well in terms of predicting financial distress than NN.

Probit and logit model was proposed for medium and large firms for forecasting insolvency by Megan and Circa (2014). Brindescu-Olariu and Golet (2013a) and Brindescu-Olariu and Golet (2013b) proposed linear MDA based on logit model for predicting financial distress. Further Machek et al (2015) developed model for bankruptcy using logit analysis and linear discriminant for verifying the risk of insolvency of firms which operate in cultural sector. Vochozka et al (2015a) developed a prediction model for financial distress which is highly effective for shipping and transportation using financial variables and logit analysis.

Bems et al (2015) developed a novel solution in firms' bankruptcy prediction like concept of changed magic square that was adopted in macroeconomics. Explanatory variables are adopted as financial ratios and Czech firms are objects. Models are compared with the help of various techniques like artificial NN, logit model, Bayes Classifiers and evolutionary algorithms. Proposed model identify the probability of expressing the outcomes of economical position of firm along with effect of specific explanatory variables. Nemec and Pavlik (2016) developed a logit model for conditions of Czech and compared the model efficiency with other foreign and Czech models on the basis of validation test. It was observed that logit model outperformed well with high efficiency of 83.97 percent.

S.No.	Author	Year	Model used	Contribution
1	Kherrazi and Ahsima	2016	binomial LR model	Using LR model, it can be predicted that failure of small sized firms is based on without permanent funds and commercial profitability.
2	Verma and Raju	2021	Logit model and MDA	Logit model performed well in terms of classification when compared with MDA
3	Iturriaga and Sanz	2015	LR and MDA	It acquired 81.73 percent accuracy with LR model before 1 year of insolvency
4	Hassan et al	2017	LR	Policy makers also gain from LR tool and it act as a tool to economical system which prevails in markets
5	Shrivastava et al	2018	Bayesian methodology and Bayesian logistic model	Bayesian logistic model was identified to perform well than conventional logistic model
6	Bems et al	2015	artificial NN, logit model, Bayes Classifiers and evolutionary algorithms	Proposed model identify the probability of expressing the outcomes of economical position of firm along with effect of specific explanatory variables

Figure 4: Logistic regression in predicting financial distress

Source: Author

2.5 Survival analysis

Gepp and Kumar (2015) carried out an investigation with CART decision tree and cox survival analysis for predicting economical distress for various uses. Cox survival analysis and CART decision were best in the classification accuracy than MDA in prediction intervals. Both methods are high classifiers than LR and its performance is poor. Techniques of survival analysis are suitable to develop a single model for making forecasting of different lengths and for analyzing the process of economical distress over time. On contrast, decision tree with non-parametric model are best to make exact forecast without risk of breaking statistical measures. Thus it can be concluded that adoption of techniques namely decision tree and survival analysis in warning systems of financial distress that are helpful to many thing in economical markets. Mousavi et al (2015) proved that model of survival analysis was higher followed by MDA and linear probability models. Thus some frameworks in modeling outperform well than other models in terms of design, as models of survival analysis are active and ability in modelling for both market based and accosting based information.

Lee (2014) adopted survival analysis for finding the major indicators in explaining the company insolvency with specific reference to Taiwan. This study adopts model of Cox proportional hazard for assessing the efficiency of market variables and conventional financial ratios as predictors in possibility of company failure to specific time. This research provides empirical outcomes with 12 economical ratios as forecasters for failure of Taiwan companies. It does not require more ratios for anticipating company insolvency. Probability model of financial distress is developed using valuation, efficiency, leverage and profitability ratio variables. Proposed method adopted survival analysis and proved that classification accuracy rate was 87.93 percent.

It was claimed by Zelenkov (2020) that survival analysis is a tool that is adopted for the problem of predicting bankruptcy. They exactly determine possible bankruptcy as well as identify the risks dependence on time with the help of censoring data. Gupta (2017) pointed out importance of survival models in prediction of default insolvency as unlike market based and conventional accounting based model, such models acquires connection between covariates and survival time. Survival model application is highly suggested for evaluating the credit risk and modelling can be performed by lenders for loans structure by acquiring the survival times of various companies across overall sample period.

Robua et al (2013) adopted Cox regression model and survival analysis for predicting the bankruptcy of firms in Roman. Major benefit of survival analysis depends on extra data it gives. Survival analysis of specific firm permits users to know about probability of firm survival ahead of given period of time. At the same time, it is not free from its restriction. Complexity of acquiring survival times that is period when fact is being estimated happens. Survival method provides good point of view when adopted for growth of prediction models in research field of bankruptcy. With inclusion of qualitative variables and audited accounts, it is probable for developing a model with best power in prediction which would help in decision making (Pereira, 2014).

S.No.	Author	Year	Model used	Contribution
1	Gepp and Kumar	2015	CART decision tree and cox survival analysis	Techniques of survival analysis are suitable to develop a single model for making forecasting of different lengths and for analyzing the process of economical distress over time.
2	Mousavi et al	2015	Survival analysis, MDA and linear probability models	Survival analysis was higher followed by MDA and linear probability models
3	Lee	2014	survival analysis and Cox proportional hazard	Proposed method adopted survival analysis and proved that classification accuracy rate was 87.93 percent.
4	Zelenkov	2020	Survival analysis	Survival analysis is a tool that is adopted for the problem of predicting bankruptcy.
5	Gupta	2017	Survival analysis, market based and conventional accounting based model	Survival model application is highly suggested for evaluating the credit risk and modelling can be performed by lenders for loans structure
6	Robua et al	2013	Cox regression model and survival analysis	Major benefit of survival analysis depends on extra data it gives.

Figure 5: Survival analysis in predicting financial distress

Source: Author

3. Discussion and Conclusion:

In India, steel industry is considered as one of main industries because of its backward and forwards connection with other sectors namely building, transportation and more. Successes of any organization rely on its potential for managing its finances efficiently. Finance is seen as most viral part in the organization. If economic performance and health is affected in the company than it affects its growth, development, sustainability and thus effective management of economic resources is needed and also needs proper attention for optimizing the financial resources. Predicting financial insolvency or distress in any company assists groups within the firms such as employees, financiers, stakeholders, customers, contractors for taking appropriate decision. Therefore, this study has identified methods or techniques for predicting financial distress in steel companies with specific reference to India. It has been identified that five techniques namely Altman Z score model, survival analysis, logistic regression, neural network and data envelopment analysis has been widely adapted by the organizations. Altman Z score model was found to be traditional method for predicting financial distress in terms of accuracy rate. In modern times, DEA and survival analysis are adopted for predicting financial distress and insolvency in companies. Neural network and logistic regression method also adopted by most of the firms for understanding the risks in bankruptcy in selected firms. Overall, it can be concluded that each model has unique feature in terms of accuracy and prediction. Based on situation, model must be carefully selected for better performance of accuracy and prediction in terms of bankruptcy, financial distress in the firms. Further this work can be extended by collecting quantitative data from the workers for studying about financial distress and insolvency.

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