Predicting Credit Ratings using Deep Learning Models – An Analysis of the Indian IT Industry

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Abstract

Due to the complexity of transactions and the availability of Big Data, many banks and financial institutions are reviewing their business models. Various tasks get involved in determining the credit worthiness like working with spreadsheets, manually gathering data from customers and corporations, etc. In this research paper, we aim to automate and analyze the credit ratings of the Information and technology industry in India. Various Deep-Learning models are incorporated to predict the credit rankings from highest to lowest separately for each company to find the best fit model. Factors like Share Capital, Depreciation & Amortisation, Intangible Assets, Operating Margin, inventory valuation, etc., are the parameters that contribute to the credit rating predictions. The data collected for the study spans between the years FY-2015 to FY-2020. As per the research been carried out with efficiencies of different Deep Learning models been tested and compared, MLP gained the highest efficiency for predicting the same. This research contributes to identifying how we can predict the ratings for several IT companies in India based on their Financial risk, Business risk, Industrial risk, and Macroeconomic environment using various neural network models for better accuracy. Also it helps us understand the significance of Artificial Neural Networks in credit rating predictions using unstructured and real time Financial data consisting the influence of COVID-19 in Indian IT industry.

Keywords: Indian IT industry, Big Data, Artificial intelligence, Credit Ratings, Multi-Layer Perceptron, COVID – 19 pandemic, Deep Learning, Financial ratios

JEL: G17

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1. Introduction

Credit Ratings are ordinal measures of a company's expected loss over the next 12 months. While they are primarily based on the issuer's current financial strength, they also incorporate expectations for its future performance. Credit ratings can help IT companies to raise funds at a lower cost. It can also help them improve their brand and increase their competitive advantage over others. These factors contribute to the overall economy's growth. In our case, they can also benefit the entity by helping them raise funds at a lower cost and attract more investors. These rating systems can help institutional investors develop public policy guidelines on how to manage their money. They can also encourage ethical behaviour by corporate borrowers. It increases market confidence and helps companies raise funds at a lower cost (Wallis et al., 2019). It allows them to make informed decisions and provides them with a better understanding of the risks involved in investing. Credit ratings help in improving a company's brand image.

The fourth industrial revolution has dramatically impacted the way financial systems operate. It has also changed the path of how businesses globally work. It is challenging for an IT company to obtain a credit rating due to the complexity of the process. Approximately 80-90% of the IT companies' financial data stands unstructured. Companies in this industry require a large team of analysts to analyze their risk profile most of the time. Many researchers believe that deep learning and statistical methods can improve credit rating predictions. In addition, many of them have shown promising results by using different statistical, machine learning algorithms. Generally, these machine learning prediction algorithms do not work efficiently with real-time financial data as the data size increases.

This paper explains the significance of deep learning artificial intelligence algorithms for predicting credit rating in the IT industry with enhanced accuracy and robustness. It also highlights the benefits of neural network algorithms while working with real-time financial data to calculate credit ratings. Various neural network techniques have been widely studied in finance to develop effective and efficient credit rating prediction tools. These include natural language processing (NLP), SVM known for their high accuracy and robustness. However, these algorithms are not yet suitable for multiclass classification. Aside from standard neural networks, deep learning models are also used in various financial fields. For instance, convolutional neural networks (CNN) and recurrent neural networks (RNN) are known to improve the performance of different financial algorithms with improved efficiencies.

However, Human intervention is more crucial to machine learning. In traditional Machine Learning techniques, most of the features that are needed to perform well are identified by a domain expert. Deep neural networks are networks with multiple hidden layers experiments with different depth networks reveal a preference for deeper networks. Deep Learning is a subset of machine learning that learns to represent the world as hierarchies of concepts, with each concept being computed in terms of more abstract ones. Thus, deep understanding has a more significant advantage over other prediction algorithms as it has higher prediction capabilities and accuracy as the dataset increases.

Due to the increasing amount of data available in Big Data, many banks and financial institutions have transformed their business models to become more robust and reliable. A reliable credit scoring model is an integral part of the decision-making process for financial agencies. Neural network-based methods are becoming more prevalent in corporate credit rating analysis. Hence Artificial Intelligence is a robust and reliable algorithm that can handle large datasets. It can train stable and predictable models while working efficiently with the real-time financial data of the companies.

The primary focus of this paper is to highlight the application of Deep learning algorithms to predict credit ratings and how accurately these algorithms work to map their efficiencies—deep learning benefits the credit lending industry in various ways like enhancing operational efficiency, using Big Data, and various new data sources in predicting the credit score. We aim to address some of these questions that we often encounter when implementing real-time financial Big Data problems.

In this study, we experimented with the performance of three neural network algorithms, which are Convolution Neural Network (CNN), Multilayer Perceptron (MLP), and Long Short-Term Memory (LSTM), to predict the credit ratings of IT Industry companies. We constructed a credit scoring model that takes into account the applicant's various financial input features. The input data in this study consists of economic variables directly obtained from the companies' balance sheets, financial statements, income statements, and Prowess IQ database. Accuracy percentages in the prediction of the credit ratings of corporate companies were mapped and compared. Out of which, MLP gained significantly higher efficiency for predicting the credit ratings accurately.

2. Literature Review

Due to the increased popularity of corporate credit ratings, studies have earlier been published in the literature which implemented various machine learning algorithms. Credit ratings are important because they provide a public service by helping people obtain information about their financial entities. These tools help investors and regulators make informed decisions regarding the entity's operations by providing a comprehensive view of a company's credit risk. It helps formulate a step towards transparency in the economy and lowers the costs associated with them. Credit ratings are incredibly powerful and valuable. They can help create an ordinal ranking for similar obligators, which is very helpful for investors and lenders. By offering a comprehensive view of an entity's credit risk profile, these tools help users make informed decisions regarding an entity's Financial Position. This transparency increases the efficiency of the economy and helps minimize information asymmetry.

They studied the relationship between machine learning and banks' credit ratings in the GCC (Mirza et al., 2020). The Neural Networks are considered second-best for the predictions made by the experts. They found that the CART is more relevant to the classifications and regression trees (Xiong et al., 2020). They used the BNN neural network as a template for their SVM method. They could get prediction accuracy of 80% for both BNN and support vector methods (Huang et al., 2004). They focused on the rating classes of US municipalities based on their neural network structures, using Moody's rating as the benchmark of their model (H'ajek, 2011). Both RNN and LSTM are widely used in finance for predicting stock price prediction. They can also be utilized for studying the environment and the market conditions (Zhuge et al., 2017).

They analyzed that multiple layers of hidden nodes characterize the deep neural networks. They are suitable for representations of complex relationships and variable interactions (Sirignano et al., 2018). Deep Learning is a method used for estimating the performance of various features of training data sets. It does so by evaluating the accuracy of the cross-validation process for forecasting credit risks (Nguyen, 2016). They studied that the counterfactual explanations provide a more detailed analysis of the data and reveal the minimal changes required to get a different result. Although counterfactuals are commonly used for changing a prediction, they can be challenging to interpret (Grath et al., 2018). They claim that their model is a globally interpretable neural network that is as accurate as any other. It is built on a decomposable model designed to be moderated into subscales for Credit rating prediction (Chen et al., 2018).

They introduced two new types of ANN and MSVM classifiers called OMANN and OMSVM. These models can handle ordinal pairwise partitioning (OPP). OMANN and OMSVM are designed to extend the capabilities of these two classes (Jae Kim, 2011). In this paper, they describe the case of an application of neural networks for credit risk assessment. They developed two systems that are both capable of handling large datasets (Angelini et al., 2007). They presented an overview of the DNNs framework and their application to predict future financial market movements. They also demonstrated their system's configuration and training approach (Dixon et al., 2017). They build binary classifiers based on deep learning models to predict loan default probability; they also performed a stability test on the models (EN Martey et al., 2018). They analyze companies from various sectors in the US by creating case studies to answer the questions presented in their paper; through ANOVA and multiple comparison tests, they were able to analyze the results (Golbayani et al., 2020).

In the above literature review, the work carried out by researchers over the globe related to credit ratings has given us an idea that machine learning algorithms can help understand the predictions. Nevertheless, it is slightly challenging for these kinds of algorithms to work with real-time financial data. The economic data keeps on changing, resulting in the change in the value of credit ratings. A large amount of data cannot be handled well by the algorithms stated in the review. Credit rating predictions require better accuracy and algorithm performance which can be achieved using deep learning models. There lies a gap of association of credit rating predictions with various artificial neural networks and deep learning algorithms, which yielded exceptional results in this experiment.

The extent of this paper is to predict the credit ratings and understand the significance of advance artificial neural networks in this area which gives us promising results compared to various machine learning and basic statistical techniques used earlier. The course of action intended by the researchers for the same are:

1. What are the factors influencing the credit ratings of IT industry in India and how are they identified?
2. What are the methods that extract the crucial features from financial data and can yield better prediction results?
3. Identification of best credit rating prediction model with highest efficiency?

3. Theoretical Background

3.1 Rating Agencies: Credit rating agencies are establishments that provide ratings on various types of debt instruments. These companies are known as publishing and dissemination firms. The agencies help investors evaluate the risk of multiple types of issuers. These agencies provide rating opinions that investors and issuers widely use. Since they do not deal with the daily operations of the markets, rating agencies have become widely viewed by investors as an independent source of information on credit risk. The agencies who published ratings for the IT industry used in this research for reference purposes are ICRA, CRISL, CARE, BRICKWORK, IND-RA.

3.2 Rating methodologies: To predict or form an opinion on the credit risks using the credit ratings published by Rating agencies mostly use statistical models and Analysts. A combination of both Analysts and mathematical models is also preferred sometimes, depending on the requirement.

3.3 Model-driven rating: Most credit rating agencies mainly focus on quantitative data, incorporating it into a mathematical model. This approach is used to evaluate the creditworthiness of various financial institutions. For instance, they might determine a bank's asset quality based on its public financial statements.

3.4 Analyst-driven ratings: A rating agency may choose to use an analyst-driven approach to evaluate a corporation or municipality's creditworthiness. This process involves analyzing various sources of information, including published reports, interviews, and discussions with the issuer's management. The analysts then apply their analytical judgment to evaluate the company's financial condition and operating performance.

TABLE 1: Corporate Credit Ratings CRISIL

AAA	Powerful capacity to meet financial commitments. It is the highest rating.
A	Strong capacity to meet commitments but subject to adverse economic circumstances.
BBB	Adequate capacity to meet commitments due to unfavorable economic conditions.
BB	It is less vulnerable to downside risks in the near term but still has significant uncertainties.
B	The rating is vulnerable to unfavorable business conditions and financial market conditions but is capable enough for managing respective financial commitments efficiently.
C	The rating is currently vulnerable to non-payable obligations. The ultimate

	recovery is likely to be lower than that of higher-rated commitments.
D	This rating indicates that an entity is in default of its debt obligations.
SD	An 'SD' rating refers to the entity's default on a specific issue or type of debt obligation but will still meet its other payment obligations.

The plus (+) and minus (-) signs are applied to compare the ratings in a specific category which ranges from 'A' to 'C.'

TABLE 2: Factors Influencing Credit Ratings of IT Industry Companies

Macroeconomic Factors	The rating assessment process begins with a comprehensive analysis of the various systemic dynamics contributing to a bank's profitability. The different systemic dynamics that determine the ratings of IT industry companies are influenced by macro-economic factors.
Business analysis and risks	This process is carried out by a team of experts who thoroughly analyze a company's operations. It involves studying the company's various risks and opportunities. The company's market position is related to its multiple characteristics such as size, structure, competition, risk, and operating efficiency. The legal Position of trustees is considered based on the terms of the prospectus and their responsibilities.
Financial Analysis and risks associated	The agency looks at various aspects of accounting quality, including evaluating multiple methods of recognizing income, expenses, and debts.
Earning protection	The profitability ratios and future earning projections of a company are considered while analyzing its earning protection.
Adequacy of Cash Flow	This metric is used to evaluate the adequacy of cash flows. It is also used to assess the current ratio, inventory to sales, and working capital management of the IT companies.
Financial Flexibility	Financial flexibility is an essential factor that rating agencies assess. It can evaluate various aspects such as capital financing plans, asset redeployment potential, and earning protection.
Competitive and Regulatory environment	The regulatory environment is analyzed in its structure, operation efficiency, and competitors' reactions to regulations.
Liquidity Management	It examines various aspects of liquidity management, including its structure, profitability, and long-term solvency. It will also look at the various components of credit risk management.
Financial Position and profitability	A company's profitability and financial Position are evaluated by considering the historic profits, spread funds, employment, profit margins, revenues, reserves, etc.
Tax Rate changes and Interest	The impact of tax rate and interest rate changes on a company's profit is analyzed. The rating process also considers the impact of future earnings and the impact of a debt burden.

4. Research Methodology

In order to answer the questions mentioned above following steps were incorporated which involve factor identification based on the earlier work been carried out in the credit rating field, unstructured data collection and data cleaning process. While in the later steps the data is brought into uniform format by nullifying the influence of COVID-19 pandemic. Also varied scale range of financial data of the companies was taken care of during these stages. Later the data was been subjected to the selected Artificial neural networks for predictions and best fit model. All these details are been explained step by step below (figure 4): -

Step 01 Factor Identification: Depending the rigorous literature review carried out various factors influencing the credit ratings were identified and depending on these factors raw data collection was been carried out.
Step 02 Raw Data collection: Raw financial Data of IT sector companies spanned from 2014 to 2020, collected from prowessIQ database, financial statements of the companies, etc. Then the historical data on the various variables for the entire period is organized in multiple ways depending on different ratings that are being categorized.
Step 03 Data pre-processing: As raw data fluctuates over time, data pre-processing is essential for developing deep learning algorithms. It is also required for the proper preparation of data for accurate predictions.
Step 04 Data discretization: The raw financial data of IT companies were initially being segmented into various segments. Part of the data was reduced, excluding the critical chunks as they influence the neural network, specifically numerical data. To minimize the COVID-19 pandemic influence, we choose the average of the past year and current year financial values for calculation.
Step 05 Data cleaning: The normalized data were then subjected to the data cleaning process. In this particular step, the missing values in the dataset were filled in. Outliers present, if any, were also being treated for the dataset to be of relevance and non-biased. If the number of null values is greater than 45 of a single IT company, we eliminated the company itself. Otherwise, we imputed the null values for the company respectively.
Step 06 Data transformation: All the values in the data set were further scaled from 0 to 1. This step helped us in maintaining uniformity among the financial data containing a varied range of scales. After the dataset was transformed into clean and relevant data, it was further divided into training and testing sets. These sets were used to evaluate the various aspects of the data. 80% of the data comprised the training set, while the remaining 20% contributed to the testing dataset.
Step 07: Model building and testing: The processed data was then subjected to the deep learning algorithms to understand how accurately they predict the credit ratings of IT companies. The figure 4 depicts a detailed process followed and explained in the methodology part.

5. Results and Analysis

Over 1761 IT Sector Company's financial data was collected, which was then subjected to data pre-processing. 1749 companies were found relevant with null values less than 45 and imputed in the next stage. Reduction of the COVID-19 pandemic, the influence was taken into consideration, and the average of the past year and current year financial values were selected for further calculations. Some of the Financial parameters considered in the credit rating predictions are Net Profit, Total Equity, Depreciation & Amortization, Net Profit Margin, Return on Assets, Selling and distribution expenses, Change in Working Capital, Profit after Tax, Cash From Operating Activities, Net PP&E, Net Intangible assets, Cash From Investing Activities, Liabilities to Equity Ratio, Cash and Cash Equivalents, Cash From Financing Activities, Short term debt, Net Change in Cash, Operating Margin, Free Cash Flow, Current Ratio, Dividends, Receivables, Current Assets, Intangible Assets, Net Goodwill, Total Noncurrent Assets, Total Assets, Current Liabilities, Total Noncurrent Liabilities.

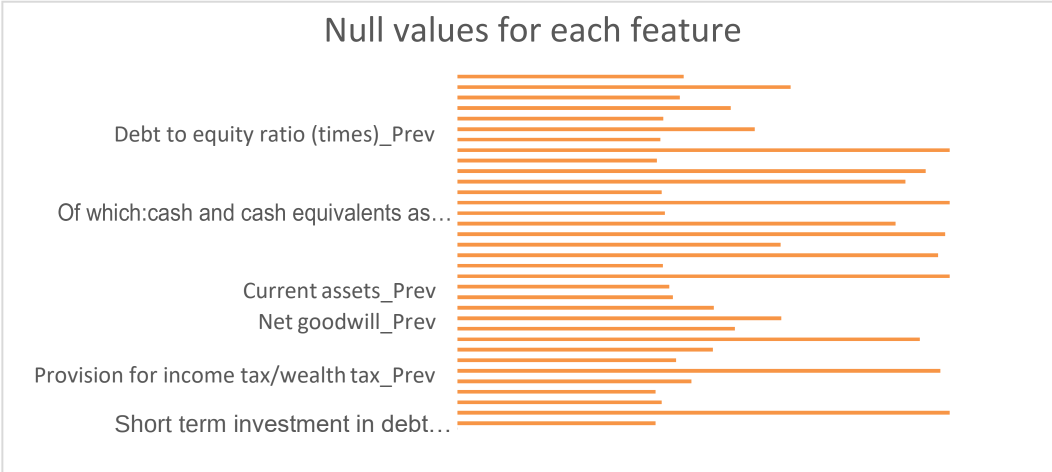

Fig 1: Null values present in financial features of the dataset

The above figure indicates the parametric distribution of null values in the data set. To preserve uniformity of the data set, we further normalized the economic importance to a scale between 0 and 1.

The above dataset was then subjected to the Multi-Layer Perceptron (MLP) model. This ensemble model does not require hyperparameter tuning. It iteratively trains its model and updates the parameters according to the partial derivative of the lost function. Limited BFGS (Broyden Fletcher Goldfarb Shanno algorithm) solver was used in the iterative method for solving unconstrained nonlinear optimization problems. It uses the Jacobian matrix and Hessian matrix to reduce the losses concerning the gradient descent. This process continues until the model reaches its convergence. The model accuracy obtained in the prediction of credit ratings is 87.8%

TABLE 3: Specifications of the Research Performed On The IT Companies Dataset for Credit Rating Prediction using MLP

Features	Value
Train Test Split	Train 80 % of data, Test – 20% of data
Solver	Limited BFGS (Broyden Fletcher Goldfarb Shanno algorithm)
Maximum iteration	250
Number of hidden layers	3
Number of nodes in each hidden layer	120,64, 32
Model accuracy obtained	87.8%

Later, to analyze the accuracy of the Convoluted Neural network for credit rating predictions, the dataset was subjected to this particular model. 80% of the data was classified into the training dataset for training the model, and the remaining 20% was used for testing purposes. The model accuracy obtained in predicting the credit ratings is 62.69%

TABLE 4: Specifications of the Research Performed On The IT Companies Dataset for Credit Rating Prediction using CNN	
Feature	**Value**
Train Test Split	Train – 80 % of data, Test – 20% of data
Model Used	CNN (Convolutional Neural network)
Number of epochs	20
Number of hidden layers	1
Number of nodes in each hidden layer	64
Activation in the hidden layer	tanh
Loss function	Categorical cross-entropy
Model accuracy obtained	62.69%

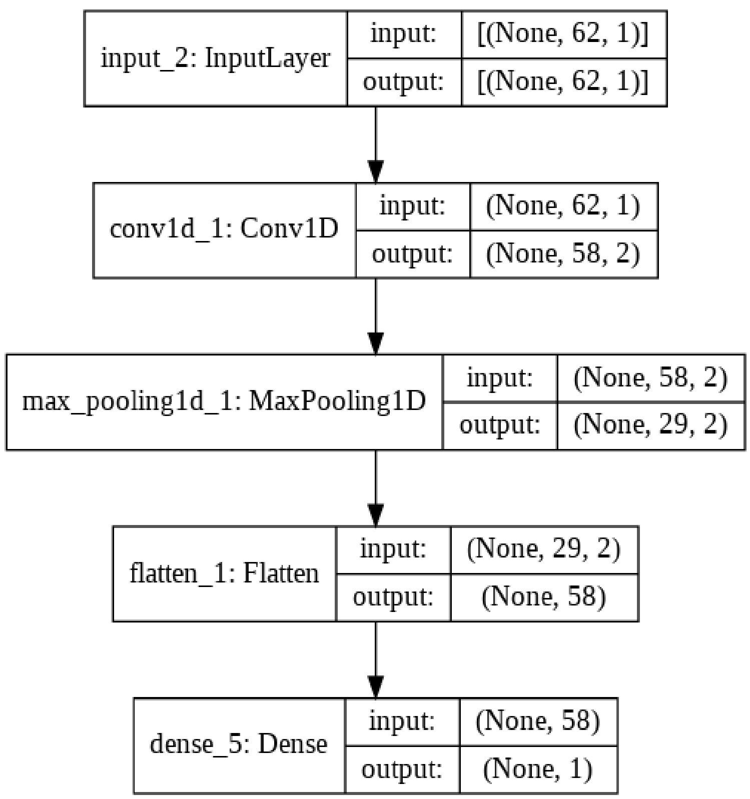

Fig 2: Neural Network model graph obtained for CNN

The number of epochs got was mainly 20. The hidden layer for this ANN algorithm was only one, while the nodes present in this hidden layer were 64. Activation in the hidden layer was tanh, while the loss function obtained was categorical cross-entropy.

The third algorithm used in our experiment was Long-Short Term memory for predicting the credit ratings. The accuracy was calculated and compared with the other two models. Similar to the other two models, the data was divided into two parts, i.e., 80% of training data and 20% of testing data. The number of epochs in this model was kept to 20, whereas the number of hidden layers was most significant among the above two algorithms. The accuracy of the model obtained in predictions was 56.7%

TABLE 5: Specifications of the Research Performed on the IT Companies Dataset for Credit Rating Prediction Using LSTM

Feature	**Value**
Train Test Split	Train 80 % of data, Test – 20% of data
Initial Layer	LSTM (Long-Short term memory)
Number of epochs	20
Number of hidden layers	4
Number of nodes in each hidden layer	64,128, 64,32
Activation in hidden layer	tanh, tanh, tanh, tanh
Accuracy of the model obtained	56.7%

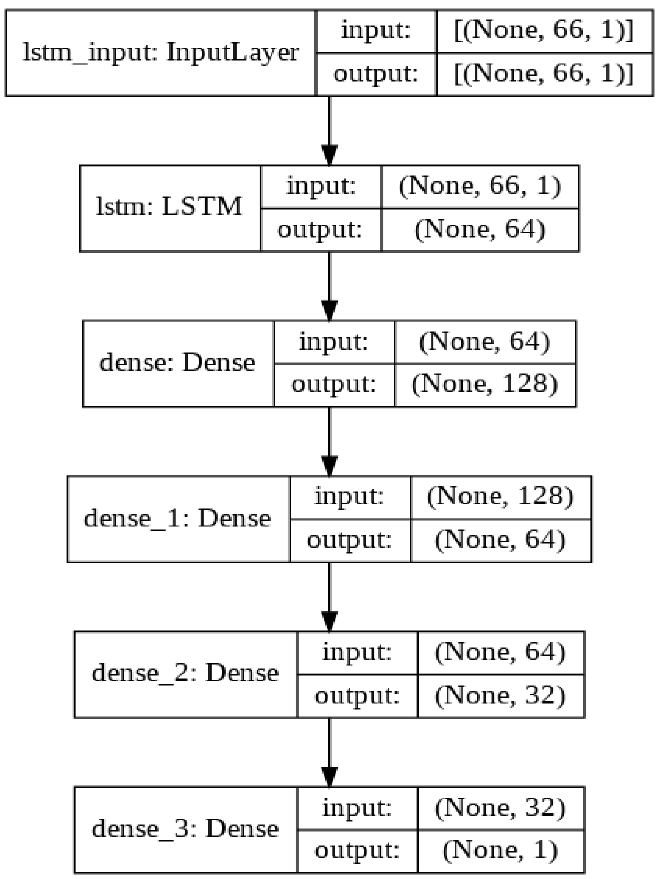

Fig 3: Neural Network model graph obtained for LSTM

Hidden layers consisted of 64, 128, 64 and 32 nodes in each, respectively. The activation in the hidden layer was of tanh.

6. Discussion and Findings

The paper contributes to understanding the significance of various neural network models in the prediction of credit ratings. The biggest challenge in building a credit scoring model is deciding which features to include to make the task more relevant. Usually, the size of data collected from different sources for the study is small concerning the number of features considered, resulting in an overfitting example. Also, there might be no significant features to the credit score that could cause the model to fail. As the financial data keeps on changing with huge volumes generated, there is a need to switch for better techniques of prediction which are robust and reliable with higher accuracy percentages. Among the three deep learning models, multi-layer perceptron gains the highest accuracy in the prediction of the ratings accurately. A multi-layer perceptron (MLP) network is one of the most common and practical artificial neural network architectures. Feature extraction of financial data can be helpful in the calculation of the ratings; thus, CNN is among those which is being used for market prediction and automatic feature selection. A credit rating can change in a quarter before it gets worse. This means that signs of distress may appear in the preceding quarters before the rating gets worse. This is because the rating does not always follow a straight line. One of the main advantages of RNN is its ability to connect past temporal observations. This is typically a requirement in credit rating predictions which let us know about the significance of LSTM in this area.

Implementing machine learning algorithms can be very time-consuming and require a lot of expertise. This paper noted that managers could easily make better decisions by predicting credit ratings based on the ever-changing financial data of IT industries. Even if managers have to shell out some costs for implementing sophisticated prediction methods, their positive effects will accrue over time. It also aids researchers in their study to implement advanced artificial neural network techniques to predict credit ratings and credit worthiness. The concept supports using credit rating models, which do not require any intervention from a human being. This method will convince others to adopt it and make better decisions based on current data.

The traditional statistical machine learning techniques used for rating prediction include logistic regression (Stepanova & Thomas, 2001; Steenackers & Goovaerts, 1989), linear discriminant analysis (Kumar & Bhattacharya, 2006; Khemakhem & Boujelbene, 2015), and Bayesian networks (Hajek, Olej, & Prochazka, 2016). The techniques provided an accuracy range of only 60% to 70% using financial statements data. However, they were not able to gather enough qualitative data to increase their accuracy meaningfully. Thus, the accuracy achieved while predicting the credit ratings for CRISL using the MLP technique in this study is 87.8%. Thus this model when used by researchers could prove to be a good tool to predict credit rating and could contribute to the body of knowledge.

7. Conclusion

This work researches the comparative study of deep learning models to help accurately predict credit ratings with an increased number of real-time financial parameters. This answers the above-mentioned scope of research. The models were evaluated on 1761 IT companies in India, depending on their efficiency. Multi-layer perceptron has the highest accuracy in predicting credit ratings. It used a BFGS solver to solve this unconstrained nonlinear optimization problem that relies on actual financial variables. Future research and implementation will be needed to produce more generalized conclusions. Data sets of other countries could be used to consolidate the results obtained from various experiments. These could include feature selection methods and different classifications algorithms.

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