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Empirical analysis of Deep Learning Model for Financial Data Prediction

Shweta Dharmadhikari, Asmita More
PICT, Pune

Abstract:- In recent years many investors are getting attracted towards stock market as a secondary source of income . Consequently, various automated financial data prediction models are being introduced for these investors. However demand for accuracy is of atmost importance in spite of involvement of many uncertainties in the aforesaid topic. With this foothold, this paper presents applications of deep learning model referred as task aware back propagation for financial data prediction. The deep learning (DL) is utilized for sensing the dynamic varying market condition for informative feature learning, after that the back propagation model which helps to reduce error and interact with deep representations in order to provide decisions to acquire the ultimate rewards in an concealed environment within taskaware back propagation through time method. Index Terms: Deep learning (DL), deep neural network (DNN), financial signal processing, neural network (NN, back propagation.

[1] INTRODUCTION

Predicting financial trades is one of the most demanding and challenging tasks due to many uncertainties involved such as economic condition, political events, investors sentiment towards a company, gold values, exchange rate, disaster, international crude oil price etc. Because of aforesaid reasons stock market is more susceptible to quick changes which cause random fluctuation in stock price. However, the stock market has always followed a haphazard pattern and its prediction is always quite a difficult task. Basically, investors prefer to undergo either fundamental analysis or technical analysis before spending money in a stock. In fundamental analysis, investors look at the intrinsic value of stocks, political climate, and the performance of the industry and economy values which helps to decide whether to invest or not. Whereas, in a technical analysis an evaluation of stocks is done by means of analyzing various statistics propagated by market activity, such as past prices and volumes is carried out. The technical analyst uses stock charts to exterminating patterns and trends which help for suggesting stock behavior in future. Prices of stocks are efficient which are helpful to predict stock prices depend on the trading data. Generally information extracted from stock prices is preprocessed efficiently and appropriate algorithms are adapted to predict the trend of the stock market which provides efficient way to analyze stock market [2].

There are many prediction models used for financial analysis. The pre-prediction model predicts market condition as positive or negative with the help of several attributes. These attributes consists of price fluctuation of fuel, commodity, foreign exchange, interest rate, general public sentiment, related NEWS and Simple Moving Average (SMA) and Auto-Regressive Integrated Moving Average (ARIMA) predicted values with help of historical data of the market. The techniques used for prediction include techniques Single Layer Perceptron (SLP), Multi-layer Perceptron (MLP) Deep Belief Network (DBN) and Radial Basis Function (RBF) and also includes techniques like Support Vector Machine (SVM), Naive Bayes and Decision Tree [3].
This paper is focusing on financial data prediction using deep learning. Deep Neural Network (DNN) is currently foundation of various applications related to an artificial neural network which are speech and image recognition, robotics, various games like chess and self-driving car, in medical section to detect cancer and in the analysis of financial signal etc [1]. The deep neural network provides an efficient processing to improve energy efficiency and throughput without sacrificing performance accuracy. The superior accuracy comes with high computational costs means that to get more accuracy DNN require general purpose compute engines like graphics processing units (GPUs) to accelerate DNN computation. DNN is a multilayer network with many hidden layers whose weights are fully connected and are often pre-trained.

The existing state of arts is discussed in Section 2. Section 3 provides details of proposed system. Section 4 highlights algorithmic flow with mathematical model. Section5 concludes this paper.

[2] LITERATURE SURVEY

This section describes existing state of arts used earlier for the financial data prediction .Subsequently; it showcases two categories vise, existing attempts using deep learning(in A. section) and without using deep learning(in B. section).
A.1) Xiumin Li, Lin Yang provides the novel approach to predict the stock closing price following the deep belief networks (DBNs) with intrinsic plasticity is elaborated. The back propagation algorithm is analyzed for output training to make minor modifications of structure parameters. The intrinsic plasticity is also enforced to the network to make it have the adaptive ability. It is postulated that IP learning for adaptive adjustment of

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neuronal response to external inputs is favorable for exaggerating the input-output mutual information [4].

A.2) Y. Deng, F. Bao, Y. Kong, deliberates deep learning in conjunction with reinforcement learning in order to defend more accuracy. The DL part benefits to sense the dynamic market condition for feature learning whereas the RL module composes trading decisions to gather together for the ultimate rewards in an unknown environment or fluctuating condition[5].

A.3) Ryo Akita, Akira Yoshihara, discusses usage of Paragraph Vector, and Long Short-Term Memory (LSTM), for financial time series forecasting. In this paper, a new avenue that novitiates newspaper articles into their distributed representations by virtue of Paragraph Vector as well as models the flashier effects of past events on opening prices about several companies with LSTM is deliberated. The performance of the avenue is substantiated on real-world data of fifty companies included on Tokyo Stock Exchange [6].

A.4) Yue Deng, Zhiquan Ren, represents fuzzy learning inclusive with DL (Deep learning) fused together to conquer uncertainty. The input is accommodated to two layers which are a fuzzy and neural network. These two prospects are fused together assembling final data representation to be classified.

This technique benefits in tasks like image categorization, financial data prediction which comprises a high level of uncertainty in raw data [7].

A.5) Jou-Fan Chen, Wei-Lun deliberates, a peculiar financial time-series analysis approach entrenched on deep learning technique is mentioned in this paper. In this paper, the main target is on the time series data processing as well as on forecasting in financial markets. Traditional feature extraction avenues in intelligent trading decision platform system are acclimated with not only with several technical indicators but also with expert rules to extract arithmetical features learning.

The most contribution of this paper is to strengthen the algorithmic trading framework with the contemplated planar feature representation methods and deep convolution neural networks (CNN) [8].

A.6) Luna M. Zhang discusses a new DNN with antithetic activation functions to globally exaggerate both parameters and task elections. In adjoining, a novel Genetic Deep Neural Network (GDNN) with multiple activation functions handles genetic algorithms to frame the parameters as well as to selects the best activation function consolidation for different neurons among many activation function consolidations through sufficient simulations. [9].

A.7) John Moody and Matthew Saffell, represents approaches for upgrading portfolios, asset allocations, and trading systems gamble on direct reinforcement (DR). In this ingression, investment decision composing is viewed as a stochastic control problem, and strategies are exposed directly. In this paper, an adaptive algorithm called recurrent reinforcement learning (RRL) for exploring investment policies which are constructive for investing is determined. The need to build forecasting models is eliminated, and better trading performance is accomplished [10].

B.1) Lean Yu, Lunchao Hu, explores a stock selection model with the pair of discrete and continuous decision variables are conferred in which a singular sigmoid-based merged discretecontinuous differential evolution algorithm is exclusively cultivated for model elaborate on [11].

B.2) Jean-Marc Le Caillec, Alya Itani ,provides fusion of two techniques is elaborated one is probabilistic and another one is possibilistic which assists to discriminate common information from consolidating technical indicators which affect overall performance. Here a choosing of technical indicators takes place through a shared / non-shared information point of view which reveals possibilistic framework which is vigorous to redundant sources than probabilistic [12].

B.3) Y. Deng, Y. Kong, F. Bao, introduces a sparse codinginspired optimal trading (SCOT) system for real-time highfrequency financial signal representation and trading. Mathematically, SCOT synchronously determines the dictionary, sparse features, and the trading strategy in a joint optimization, acquiescent most advantageous feature embodiment for the specific trading intention. The learning process is sculpted as a bi-level optimization and interpreted by the online gradient descend method with exceptional convergence. In this dynamic situation, the system is recognized on the real financial market to trade the index futures in the Shanghai exchange centre [13].

B.4) Chia-Hsuan Yeh and Chun-Yi Yang, investigates of how behavioral in terms of mimetic strategy learning within a social network which influences the asset price dynamics is presented. Here two attributes are elaborated, first is genetic programming algorithm, in which traders are characterized by bounded rationality and their adaptive learning behavior is interpreted by the. Second, the traders are referring to heterogeneous based on their positions in social networks. Mimetic learning takes part in local collaborations among traders which are directly tied with each other when they are approaching their trading policy according to the relative performance of their own and their neighbor's [14].

B.5) Desheng Dash Wu, Lijuan Zheng, introduces novel sentiment ontology which manipulates context-sensitive sentiment analysis of online opinion posts in stock markets. This technique merges sentiment analysis into machine learning accesses established on support vector machine and generalized autoregressive conditional heteroskedasticity modeling, which consequences in the solid interconnection between stock price volatility trends as well as stock forum sentiments towards stock trends. Computational concludes show that the statistical machine learning avenues has higher classification accuracy than that of the semantic approach [15].

B.6) Mukesh Kumar Mehlawat and Pankaj Gupta, addresses the contention of portfolio picking with fuzzy parameters from a paranoiac of chance constrained multiobjective programming. The model intended to two statistical ratio, maximum return (short term as well as long-term) and liquidity of the portfolio trends. It does so at integrity, which is no less than the confidence levels scrutinized by the investor. Further, to grasps dubious nature of the financial markets more realistically, fuzzy parameters elaborated here are such as those synthesized by general functional forms [16].

B.7) Li-Xin Wang, introduces price dynamical model with big buyers and big sellers by elaborating two trading strategies: (i) Follow-the-Big-Buyer which buys when big buyer begins to emerge and there is no gesture of big sellers, holds the stock as long as the big buyer is still there, and sells the stock once the big buyer dissolve; and (ii) Ride-the-Mood which buys when the big buyer firmness begins to outpace the big seller firmness , and sells the stock once the contradictory happens [17].

B.8) Linda Ponta, Enrico Scalas, Marco Raberto, and Silvano Cincotti, simulates of high-frequency market data is Heterogeneous agents trade a precarious asset in exchange for cash. Agents have zero intelligence or less knowledge as well as issue random limit or market orders demoralizing on their budget constraints. The price is unwrapped by means of a limit order book. A renewal order-generation process is descended having a waiting-time distribution amidst consecutive orders that postdate a Weibull law. The reproduction of decision show that this mechanism can emulate fat-tailed distributions of returns externally ad-hoc developmental presumptions on agents [18].

B.9) Stelios D. Bekiros, discusses the efficiency of a trading approaches established on the implementation of a neurofuzzy model which advices to forecast the direction of the market in case of FTSE100 and New York stock exchange returns (NYSE)[19].

B.10) Adam Ghandar, Zbigniew Michalewicz and Martin Schmidt, introduces least squares support vector machine (LSSVM) learning integrated with the mixed kernel which helps to analyze stock market trends. In the proffered learning a genetic algorithm (GA) and evolutionary algorithms (EAs), is pre-owned to select input attributes for LSSVM learning. After that additional parameters augmentation of LSSVM is done with help of GA [20].

B.11) Adam Ghandar, Zbigniew Michalewicz, Martin Schmidt, Thuy-Duong To**,** elaborates a robust computational intelligence system for learning trading rules as well as the methods. Although in dynamic market conditions, the fuzzy logic rule base is pre-owned to express the trading rules and with help of artificial evolutionary process, the system determines to form rules that can perform well for prediction of trends. In both financial industry and academia a comprehensive investigation of the outcome of applying the system for portfolio construction with help of portfolio evaluation tools widely useful [21].

B.12) William Leigh, Cheryl J. Frohlich, Steven Hornik, Russell L, discussed an efficient market hypothesis (EMH) is an essential quality of financial economics. The EMH asserts implements all available information of security prices fully emulate and fair values that of the stock market prices securities. Because of this investors cannot persistently "beat the market" due to stocks endure in perpetual equilibrium, which makes research efforts pointless. Technical analysts preowned for partially analyze future stock price by analysing past stock prices, can undeviating achieve a trading return that outperforms the stock market average return [22].

B.13) Kai Keng Ang, Chai Quek ,investigates the method of forecasting stock price difference on which are generated by price series data using neuro-fuzzy systems and neural networks. It also proposes a neuro-fuzzy stock trading decision model called stock trading using rough set-based pseudo outer-product (RSPOP) which together finds the price difference forecast method with a forecast bottleneck free trading decision model [23].

B.14) Blake LeBaron, analyze some of the empirical features provoked in an agent-based computational stock market with market participants accommodating and emerging over time. Investors view contradicting lengths of past information as being significant to their investment decision making process. The interrelating of these memory lengths in devising market prices formulate a kind of market ecology in which it is challenging for the more stable longer horizon agents to take over the market. What arises is a dynamically fluctuating market in which various types of agents arrive and evacuate depending on their current relative achievement. This paper interprets several key time series aspects of such a market. It is graded to the variability and growth of dividend payments in the United States. The market accomplishes some aspects that are remarkably related to those from actual data. These include amplifying the volatility from the dividend process, activating persistence in volatility and volume, and developing fat-tailed return distributions [24].

B.15) Jerry felsen, discussed most of the investment analysis associated with decision making by weighing the evidence. Such decision mechanisms can be established with the aid of pattern recognition (PR) techniques. Specifically, here method applied is generalized perceptron-type PR techniques to both general markets estimating and investment selection. And after the investment decision system has been enforced and put into operation, its performance is then gradually enhanced through learning from previous decision making experiences. Here iterative probabilistic learning algorithms (based on stochastic approximation techniques) have been invoked. Decision models for both investment selection and market forecasting have been accomplished and examined in actual investment analysis, which results in an indication of the aid of PR techniques having an above average investment performance [25].

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Table no.1 Summary of Literature survey

Sr. No	Title	Publication & Year	Author	Merits and techniques	Demerit &conclusion
1	Deep Direct Reinforcement Learning for Financial Signal Representation and Trading[5]	IEEE transactions on neural networks and learning systems 2017.	Yue Deng, Feng Bao, You yong Kong, Zhiquan Ren, and Qionghai Dai, Senior	This advantage is due to the automatic feature learning mechanism of DL.	For real time system due to financial market is not stationary
2	Social Networks and Asset Price Dynamics[14]	IEEE transactions on evolutionary computation, vol. 19, no. 3, June 2015	Chia-Hsuan Yeh and Chun-Yi Yang	It is prudent for policy makers to examine the current financial situations regarding the characteristics of market and traders	False mouth communication
3	Dynamical Models of Stock Prices Based on Technical Trading Rules Part III: Application to Hong Kong Stocks[17]	IEEE Trans. on Fuzzy Systems 23(5): 1680-1697, 2015.	Li-Xin Wang	profit advances and risk reductions	Imprecision tolerance more and adaptability less.
4	Sign Prediction and Volatility Dynamics with Hybrid Neurofuzzy Approaches[19]	IEEE transactions on neural networks, vol. 22, no. 12, December 2011	Stelios D. Bekiros	The proposed volatility-based neurofuzzy model, might allow investors to earn higher returns than the passive portfolio management strategy.	Imprecision tolerance more and adaptability less.
5	Sparse Coding-Inspired Optimal Trading System for HFT Industry[13]	IEEE transactions on industrial informatics, vol. 11, no. 2, April 2015	Yue Deng, Youyong Kong, Feng Bao, and Qionghai Dai, Senior Member, IEEE	The dictionary learned from SCOT is very robust in coping with the intraday price heterogeneity.	Hard to apply offline training to SCOT due to lack of full knowledge
6	Context-Dependent Pre-Trained Deep Neural Networks for Large-Vocabulary Speech Recognition[28]	IEEE transactions on audio, speech, and language processing, vol. 20, no. 1, January 2012	George E. Dahl, Dong Yu, , Li Deng,and Alex Acero,	Provide dramatic improvements in recognition accuracy	
7	Deep learning for stock prediction using numerical and textual information.	IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS), Pages: 1 – 6, Year: 2016.	Ryo Akita, Akira Yoshihara, Takashi Matsubar	The performance of the proposed avenue is validated on real-world data	Difficult to deal with vanishing gradient issue.

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9	Financial Time-series Data Analysis using Deep Convolutional Neural Networks	2016 7th International Conference on Cloud Computing and Big Data, Pages: 87 – 92, Year: 2016	Jou-Fan Chen, Wei-Lun Chen, Chun-Ping Huang, Szu-Hao Huang	The major contribution of this paper is to enhance the algorithmic trading framework with the proposed planar feature representation methods	Require several technical indicators and expert rules to extract numerical features.
10	Genetic Deep Neural Networks Using Different Activation Functions for Financial Data Mining	2015 IEEE International Conference on Big Data (Big Data), Pages: 2849 – 2851, Year: 2015	Luna M. Zhang	novel Genetic Deep Neural Network (GDNN) with different activation functions uses genetic algorithms	Explained different activation function consolidation for different neurons among many activation function combinations
11	Learning to Trade via Direct Reinforcement	IEEE transactions on neural networks, vol. 12, no. 4, July 2001	John Moody and Matthew Saffell	recurrent reinforcement learning	The need to build forecasting models is eliminated, and better trading performance is achieved
12	Stock Selection with a Novel Sigmoid-Based Mixed Discrete-Continuous Differential Evolution Algorithm	IEEE transactions on knowledge and data engineering, vol. 28, no. 7, July 2016	Lean Yu, Lunchao Hu, and Ling Tang	sigmoid-based mixed discrete-continuous differential evolution algorithm	A stock selection model with both discrete and continuous decision variables.
13	Stock picking by Probability-Possibility approaches	IEEE Transactions on Fuzzy Systems, Volume :25, Pages: 333 – 349, June 2016	Jean-Marc Le Caillec, Alya Itani, Didier Gueriot	two techniques is involved one is probabilistic and another one is possibilistic	Merging of two techniques helps to discriminate common information which affect overall performance
14	A Decision Support Approach for Online Stock Forum Sentiment Analysis	IEEE transactions on systems, man, and cybernetics: systems, volume: 44, pages: 1077 – 1087, year: 2014.	Desheng Dash Wu, Lijuan Zheng,	Introduces novel sentiment ontology which conducts context-sensitive sentiment analysis of online opinion posts in stock markets	Integration of sentiment analysis into machine learning approaches based on support vector machine
15	Fuzzy Chance-Constrained Multiobjective Portfolio Selection Model	IEEE transactions on fuzzy systems, vol. 22, no. 3, June 2014.	Mukesh Kumar Mehlawat and Pankaj Gupta	Fuzzy system	Portfolio picking with fuzzy parameters from chance constraints.

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16	Statistical Analysis and Agent-Based Microstructure Modeling of High-Frequency Financial Trading	IEEE journal of selected topics in signal processing, vol. 6, no. 4, August 2012.	Linda Ponta, Enrico Scalas, Marco Raberto	simulation of high-frequency market data is achieved	Hard to apply offline training due to lack of full knowledge
17	Computational Intelligence for Evolving Trading Rules	IEEE transactions on evolutionary computation, vol. 13, no. 1, February 2009.	Adam Ghandar, Zbigniew Michalewicz,	least squares support vector machine (LSSVM) learning fused with the mixed kernel	Here genetic algorithm and evolutionary algorithms is used to select input features for LSSVM learning.
18	Trading with a Stock Chart Heuristic	IEEE transactions on systems, man, and cybernetics—part a: systems and humans, vol. 38, no. 1, January 2008	William Leigh, Cheryl J. Frohlich,	efficient market hypothesis	The EMH asserts provides all available information of security prices fully reflect and fair values that of the stock market prices securities
19	Empirical Regularities from Interacting Long- and Short-Memory Investors in an Agent-Based Stock Market	IEEE transactions on evolutionary computation, vol. 5, no. 5, October 2001.	Blake Le Baron	empirical features	
20	Learning Pattern Recognition Techniques Applied to Stock Market Forecasting	IEEE transactions on systems, man, and cybernetics, vol. smc-5, no. 6, November 1975	Jerry felsen	pattern recognition (PR) technique	PR techniques having an above average investment performance

[3] PROPOSED APPROACH

Figure no. 1 shows the architectural flow of proposed system. First, we load data from the dataset which is readily available on various website like Github, BSE, yahoo fiancé. Then applying parsing and tokenization after that we train module by feed forward and back propagation then detect the threshold value and predict the condition of the stock market. Using graph, it is easy to show predicted values. Deep-neural networks are distinguished from the more commonplace single-hidden-layer neural networks by their number of node layers through which data passes through a multistep process. Traditional machine learning relies on shallow nets, which has one input and one output layer, and only one hidden layer in between them. More than three layers (including input and output) qualify as "deep" learning. So deep is defined in the technical term that it involves more than one hidden layer between input and output. In deep-neural networks, each layer of nodes trains based on a distinct set of features of the previous layer's output. The furthermore advance into the neural network, the more complex the features add nodes which help in reorganization since they are doing an aggregation and recombination of features from the previous layer.

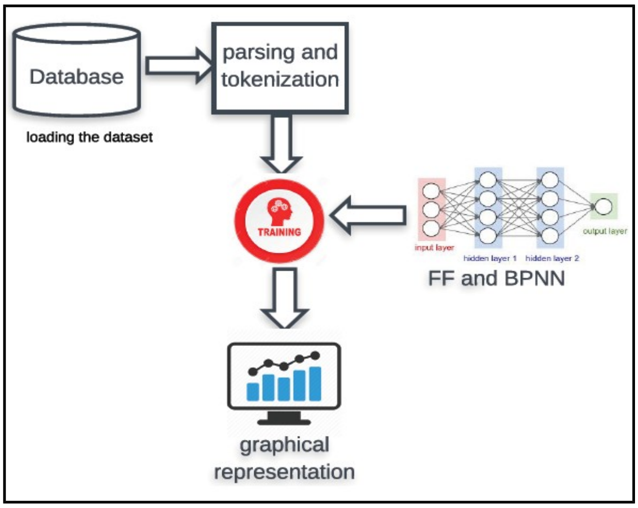

Figure no.1 Architectural flow

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[4] MATHEMATICAL EXPRESSION AND ALGORITHM

4.1] MATHEMATICAL EXPRESSION:

Consider S be the system which includes following attributes,

$S = \{U, I, I_d, I_o, s, f, F\}$

U be set of users where $U = \{U_1, U_2 \ldots U_n\}$

I be input neurons $I = \{I_1, I_2 \ldots I_n\}$

I_d set of hidden neurons $I_d = \{I_{d1}, I_{d2} \ldots I_{dn}\}$

I_o output neurons.

s is success condition.

F is failure condition.

For detection and training module we use following equations sets.

F be the set of function

$F = \{F_1, F_2 \ldots F_n\}$

F_1 =loading data

F_2 =parse and tokenization

F_3 =getting random weight

F_4 =calculating delta

- Define total layers L, input neuron N and hidden neuron N'
- Prepare network by connecting axons to each neuron accordingly.
- Assign random weights Wi for each neuron.
- Calculating values for next neuron

$$W = \sum W_i * X_i \quad \ldots (1)$$

Where Wi=weight of node or axons

Xi=input values of incoming neuron

- Repeat up to last layer.

Apply limitor function

$$F(x) = 1/(1+e^{-x}) \quad \ldots(2)$$

Then calculating error

$$\Delta = (T-O)*((1-O)*O) \quad \ldots(3)$$

Where T=target and O=output

- Calculating new weight of each node

$$W^{+}_{AB} = W_{AB} + (\text{Error} \;\; x \;\; \text{Output}_A) \quad \ldots (4)$$

Where W^{+}_{AB} = new weight

W_{AB} = old weight

- Apply same procedure to all nodes.

5] RESULTS AND COMPARATIVE STUDY

5.1Graphical representation of various technical indicators:

5.1.1 With respect to organization:

4.2] ALGORITHM:

Input: From data set

Output: Prediction of financial market

Procedure:

1.Define total layers L, input neuron N and hidden neuron N'

2. Prepare network by connecting axons to each neuron accordingly.

3. Assign random weights Wi for each neuron.

4.Calculating values for next neuron by using equation (1)

5.Repeat up to last layer and apply limitor function shown in equation(2)

6.Then calculating error with the help of equation (3)

7.Calculating new weight of each node by equation(4)

8. Apply same procedure to all nodes.

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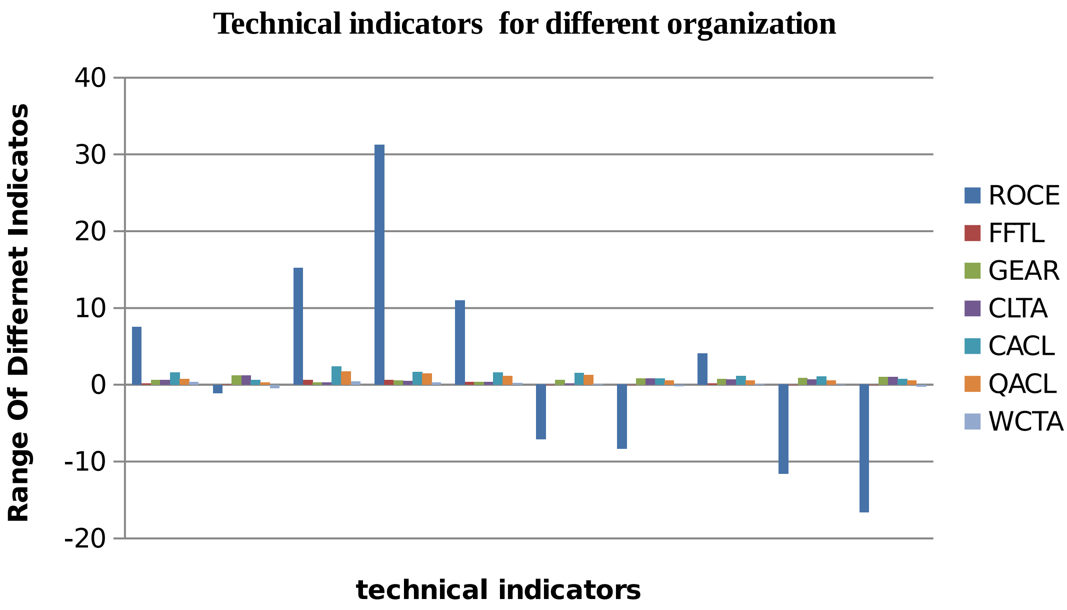


Figure 6.3Graph with respect to organization

6.3.2.2 Range of technical indicators to detect bankruptcy:

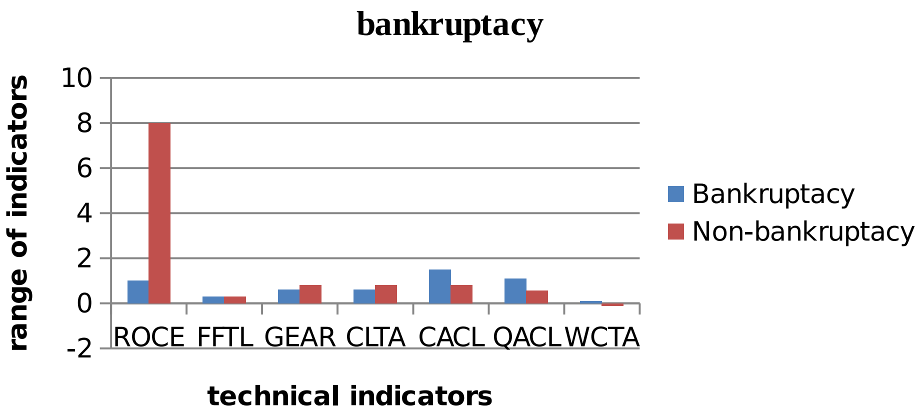
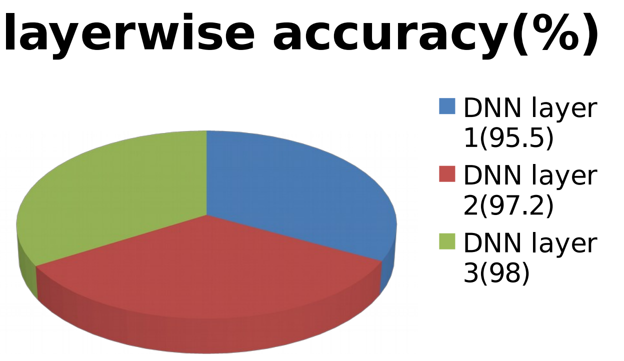


Figure 6.4 Graph of range technical indicators

Table 6.2: Layers comparison with accuracy

Sr. no.	Layers	Accuracy (%)
1	DNN layer 1	95.5
2	DNN layer 2	97.2
3	DNN layer 3	98



[6] CONCLUSION

In this study, deep neural network ensemble is used to predict bank related data. Deep-neural networks are distinguished from the more commonplace single-hidden-layer neural networks by their number of node layers through which data passes through a multistep process. The relative errors of predicted indices and actual indices, as well as the accuracy of trend predictions, are calculated to measure the performance of predictions. The stock market has always followed a haphazard pattern and its prediction is always quite a difficult task. A large number of different techniques and algorithms are available for prediction of trade of stock market but here we focused on the deep neural network. The deep neural network provides an efficient processing to improve energy efficiency and throughput without sacrificing performance accuracy. As the name indicates deep learning it uses multiple hidden layers, so it improves accuracy. For training purpose feed forward and back propagation used which helps to minimize error rate. Due to this technique, overall prediction accuracy improved.

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