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Statistical Approach in Indian Capital Market through Quantitative Modeling of Quarterly Financial Metrics Using Deep Learning

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Abstract: The use of computing power in stock market analysis has been a popular field of research for investors and retailers seeking to maximize their profits from the market. However, there is limited research on the relationship between quarterly financial results and future stock price movements for companies listed on the National Stock Exchange in India. This study aims to fill this knowledge gap by examining this relationship and analyzing the impact of key technical and fundamental parameters on future stock prices. Data scraping techniques were used to collect quarterly results and stock price data, and the analysis showed that the proposed model provided an average profit of 142% over a three-year period, with an annual profit of 34.7%. The neural network model achieved a 62.9% accuracy on the test dataset. Improvement opportunities exist for higher accuracy. The experimental results demonstrate that the proposed model can play a vital role in stock price prediction and could be useful for investment decision-making. Overall, this study provides valuable insights into the impact of stock fundamentals on stock prices and could be a valuable resource for investors and retailers seeking to maximize their profits from the stock market.

Keywords: *Quarterly results, Fundamental Analysis, Stock Price Prediction, Technical Analysis, Deep Learning*

1. Introduction

The stock market has been a crucial aspect of the global economy. It serves as a medium for investors to participate in the growth of companies without working in it. The stock market is impacted by diverse factors that can affect its performance, companies' fundamental data is one of them. Fundamental analysis has been widely used to predict the future performance of a company based on past data analysis. Fundamental analysis involves examining a company's financial statements, management, and industry to determine its intrinsic value. Fundamental analysis provides insights about the company's health and growth potential.

In this study, we aim to provide insights about how the company's quarterly financial results impact its future price. Since there are so many parameters involved in financial results, we only focused on financial parameters - margin, EBITDA, profit, revenue, EBIT, moving average trend and Equity Share Capital - to understand their impact on a company's stock price. We collected data on over 1,500 companies registered on the National Stock Exchange in India (NSE), covering a period of three years. Using a classification system based on changes in financial parameters, we analyzed the net change in stock prices over the next three months after each quarter's results.

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1.1 Descriptions of the financial factors used in the study-

Margin: In the stock market, the term "margin of a company" typically refers to a company's profit margin or net margin. Profit margin is a financial measure that quantifies the profitability of a company's operations by calculating the percentage of revenue that remains as profit after deducting all expenses. The profit margin is determined by dividing the net income (profit) of a company by its total revenue and expressing it as a percentage.

EBITDA: It stands for "Earnings Before Interest, Taxes, Depreciation, and Amortization". It is a financial indicator commonly used by businesses to assess their operating performance and profitability. EBITDA provides a snapshot of a company's ability to generate income from its core operations, excluding non-operating factors like depreciation, taxes, interest, and amortization.

Total Profit: It is the difference between a company's revenue and expenses. It can be calculated in different ways, such as operating profit, net profit, or gross profit, depending on the specific expenses that are considered. Profit is an important measure of a company's financial performance and is often used to evaluate its profitability.

Revenue: It is the overall money generated by a company from the sale of its services or products. It is often used as an indicator of a company's size and growth potential.

EBIT: EBIT stands for "Earnings Before Interest and Taxes." It quantifies a company's profitability that looks at its earnings before these expenses are deducted. EBIT is often used to compare the performance of companies in different industries or with different capital structures.

Simple Moving Average (SMA): It is a widely used statistical technique to analyze time series data. It is a calculation that measures the average value of a series of data points over a specific period, where the window of the period moves along with the data series. The simple moving average smooths out the fluctuations in the data series, making it easier to identify trends and patterns over time.

Equity Share Capital: It refers to the amount of money that a company raises from selling shares of its common stock to investors. Equity shareholders hold ownership in the company and are entitled to share in its assets and profits. The amount of Equity Share Capital that a company has can affect its financial position and ability to raise additional funds.

PE ratio: The PE ratio, or Price-to-Earnings ratio, is a widely used financial metric in the stock market that helps investors assess the valuation of a firm's stock. It is determined by dividing a company's current market price of stock by its earning per share (EPS). EPS represents the proportion of a company's profit that is allocated to each outstanding share of common stock. It represents the company's earnings generated for each share of stock.

Nowadays, with the advancement in computing power, several research have been made to forecast the prices using deep learning and machine learning techniques. Pengfei Yu et al. [1] presents a DNN-based model for predictive analysis of stock prices, achieving higher accuracy. Yuxuan Huang el al. [2] used stock fundamentals for the comparison of FNN and ANFIS for stock prediction using financial ratios; FNN shows superior performance. O Bustos et al. [3] provides a systematic review of forecasting techniques, including Deep Learning and Text Mining, used for predicting stock market movement from 2014 to 2018.

The contribution of the proposed paper are:

- To provide insights for the prediction of future selling and buying patterns in the stock market.
- A statistics-based analysis on financial parameters of individual companies including revenue, EBITDA, profit, and margin.
- Encourages other researchers to explore this area using diverse techniques.

2. Literature Review

Given the significance of analyzing and forecasting the stock market to facilitate informed investment decisions, numerous scholars have been drawn towards this area of research. Many studies have been conducted to develop accurate prediction models that can help investors reduce investment risks and select profitable stocks.

Zhigang Jin et al. [4] have proposed a novel deep learning model that considers investors' emotional tendencies in predicting stock market trends. The model incorporates empirical modal decomposition to break down stock price data and uses LSTM with an attention mechanism to examine the interdependencies among sequential data points over time. The study shows that this revised LSTM model improves prediction accuracy and reduces time delays. Isaac Kofi Nti et al. [5] review 122 research papers utilizing machine learning techniques for the analysis of stock prices. Technical analysis is the most used method, with SVM and ANN being the most popular algorithms. Wasiat Khan et al. [6] used machine learning algorithms for predictive analysis of stock prices using social media and data from financial news, with feature selection and spam tweet reduction. It identifies which forecasting markets prove challenging as they are subject to the influence of financial and social media news, adding to their unpredictability. The predicted model got an accuracy of 75.16% and 80.53% using news related to finance and social media news, respectively.

Andrea Picasso et al. [7] discusses the challenge of stock market prediction and how fundamental and technical analysis approaches have emerged. The article proposes a machine learning technique to combine both approaches and uses data from technical indicators and sentiment analysis of news articles. The result is a predictive model that forecasts the of 20 companies registered in the NASDAQ100 index. The effectiveness of the approach is demonstrated through a high-frequency trading simulation, with an annualized return of over 80%. Xiaodong Li et al. [8] proposed a stock prediction system using technical and sentiment analysis through a deep learning model. The results show improved accuracy using both indicators, outperforming baselines, and single-indicator models. The Loughran-McDonald Financial Dictionary outperformed other sentiment dictionaries. Adil MOGHAR et al. [9] introduced a novel model for predictive analysis of stock prices with higher accuracy, specifically using RNN and LSTM. The proposed model was employed for the prediction of values for GOOGL and NKE stock prices and showed good results in predicting opening prices. Anita Yadav et al. [10] addresses the research gap by optimizing an LSTM model on an Indian stock market dataset. Mehar Vijh et al. [11] used Random Forest and ANN models to forecast the upcoming day closing prices of stocks for 5 companies from different sectors using financial data. The models achieved good accuracy as evaluated by RMSE and MAPE. A. H. Bukhari et al. [12] proposed a new hybrid model combining fractional order derivative and deep learning LSTM networks for predicting fast fluctuating and high-frequency financial data. The proposed model, which combines ARFIMA and LSTM, extracts profound features and models nonlinear functions, minimizes volatility and overfitting problems, and achieves around 80% accuracy on Root Mean Square Error (RMSE) compared to traditional forecasting methods. M. Nabipour et al. [13] conducted a study to mitigate the potential risk of forecasting stock prices in the stock market. They compared nine machine learning models and two deep learning methods using ten technical indicators and historical data of ten years. The study found that LSTM and RNN models performed better than other models, with a significant difference for continuous data. This suggests that deep learning techniques can be useful in accurately predicting trends in the stock market and may help investors make more informed decisions. K. Zhang et al. [14] introduced a new architecture for Generative Adversarial Networks (GANs) in stock market prediction. The generator component of the model employs Long Short-Term Memory (LSTM), while the discriminator component utilizes Multi-Layer Perceptron (MLP). The study found that the proposed GAN model outperformed other models based on machine learning and deep learning methodologies in predicting daily closing prices of S&P 500 Index and several stocks. This approach presents a promising method to improve the accuracy of predicted prices of stocks and could potentially provide valuable insights for investors. E. Hoseinzade et al. [15] proposes a framework based on Convolutional Neural Networks (CNN) for extracting features in financial data to predict market trends. The framework considers the interconnection between diverse markets as an informative source for selecting features. The proposed method outperforms existing baseline algorithms, achieving better prediction performance. V. Tyagi et al. [16] proposes a CNN-LSTM model with pre-trained embedding to automatically extract features for sentiment analysis and review classification. The accuracy of the model was 81.20%. P. R. Charkha et al. [17] analyzes the use of feedforward and neural networks with radial basis functions networks to predict stock's price trends and values based solely on past prices, without using fundamental or technical data. ANN was used for learning.

P. Gao et al. [18] introduces four machine learning methods, including MLP, LSTM, CNN, and an attention-based neural network, to forecast the future day's index price by three financial markets using historical technical indicators, trading data and macroeconomic variables. The attention-based model performs best, and all models perform better in developed markets than in developing ones. T. Kimoto et al. [19] presented a system designed to predict optimal timing for buying and selling on the Tokyo Stock Exchange based on modular neural networks, using various algorithms for learning and methods for prediction. A. H. Moghaddam et al. [20] examines the capability of feedforward artificial neural networks trained by the backpropagation algorithm to forecast the daily NASDAQ stock exchange rate by utilizing recent historical stock prices and incorporating the day of the week as input factors. Two networks were developed and validated using four and nine prior days of input data. The study used NASDAQ data from January to June 2015. Mahla Nikou et al. [21] conducted a study to compare the prediction power of four machine learning algorithms for forecasting stock market trends. The researchers employed the daily closing price data of the iShares MSCI United Kingdom exchange-traded fund spanning from January 2015 to June 2018. The study found that deep learning outperformed the other methods when forecasting the stock market trends. This suggests that deep learning techniques can be useful in accurately forecasting market trends and may help investors make more informed decisions. Xiongwen Pang et al. [22] proposes an inventive neural network-based methodology to predict the stock market. The use of deep learning and "stock vector" allows for data analysis. The deep LSTM with embedded layer model provides better accuracy in anticipating the performance of the stock market. Weiwei Jiang et al. [23] survey provides an overview of recent studies on deep learning models for stock market prediction. Additionally, the survey identifies potential areas for future investigation in this domain. By summarizing the current state-of-the-art in deep learning approaches for forecasting stock market movements, the survey provides valuable insights for practitioners and researchers interested in this area.

Wen Long et al. [24] introduces a new model, the multi-filters neural network (MFNN), to extract features and predict price movements in temporal data in the financial domain. The MFNN combines recurrent and convolutional neurons to gather data extracted from diverse feature spaces and market perspectives, resulting in improved accuracy, profitability, and stability compared to other models. Kaustubh Khare et al. [25] focuses on using technical analysis and deep neural networks to forecast short-term prices of ten stocks on the NYSE. The study compared feed-forward neural networks and recurrent neural networks, finding that feed-forward multilayer perceptron models outperform LSTM models in predicting short-term prices. Guanzhi Li et al. [26] proposed the PCC-BLS framework, to tackle the challenge of accurate stock price prediction by employing a multi-indicator feature selection method. Through evaluation on stocks from Shanghai and Shenzhen Stock Exchanges, the approach outperformed ten other machine learning methods. Yu Zhao et al. [27] proposed DanSmp, a Dual Attention Network, to address the challenging task of predicting stock movement. By constructing a comprehensive Market Knowledge Graph (MKG) and utilizing momentum spillover signals, the proposed approach improves stock prediction performance. Experimental evaluations against nine state-of-the-art baselines demonstrate the effectiveness of DanSmp with the constructed MKG. Heyuan Wang et al. [28] proposed HATR-I, a Hierarchical Adaptive Temporal-Relational Interaction model, which captures short- and long-term transition regularities using dilated convolutions and gating paths. We incorporate dual attention and edge attributes to refine inter-stock collaborative information. Our model identifies significant feature points and scales considering time attenuation. Additionally, we optimize stock representations by deducing latent shared clusters. Experimental results on real-world datasets validate the effectiveness of our proposed model.

3. Methodology

Numerous observations and evidence suggest that the market trend frequently shifts following the announcement of quarterly results. The authors of this paper are investigating a potential correlation between a stock's quarterly results and its future price movement, which could provide insight into the stock market's future pattern.

3.1. Data Collection

The process of collecting and analyzing financial data is a crucial component of any business or investment decision. In this case, the data collection process was extensive and thorough to ensure that the analysis conducted would be reliable and meaningful. The first step was to collect stock price data for over 1000 companies registered on the NSE for the previous three years. This process involved gathering data from multiple sources to ensure that the dataset was comprehensive and complete. In addition to stock price data, quarterly results data was also collected through web scraping of the Money control website. This website provided valuable information on various financial parameters such as margin, EBITDA, profit, revenue, EBIT, and Equity Share Capital. By collecting this data, it was possible to attain a thorough comprehension of the financial health of the companies in question, and their performance over time.

3.2. Data pre-processing

Once the data was collected, it underwent a rigorous cleaning process to remove missing or duplicate entries. This step was critical in ensuring the accuracy and reliability of the dataset. Furthermore, the data underwent normalization to ensure uniformity in the analysis process. Normalization involves adjusting the values in the dataset to a common scale to enable meaningful comparison and analysis. This process ensured that the data was reliable, and any analysis conducted on it would be meaningful and valuable. The data collection process was time-consuming and required significant effort, but it was necessary to ensure that the analysis conducted would be accurate and reliable. By following a comprehensive approach, the data collected was robust, reliable, and could be used to conduct in-depth financial analysis. The analysis conducted using this dataset could provide valuable insights into the financial health of the companies in question and inform business and investment decisions. Therefore, it is essential to prioritize and invest in data collection processes to obtain reliable and meaningful data for analysis.

Throughout the process of data collection, the gathered data underwent preprocessing using the Python and Pandas library. The data cleaning process removed any missing or duplicate data, ensuring that the data was accurate and reliable. The financial data for each quarter, which included margin, profit, EBITDA, revenue, EBIT, PE ratio, and Equity Share Capital, was normalized by calculating the percentage change in prices with respect to the previous quarter. This normalization process helped to standardize the data, enabling meaningful comparison and analysis.

The 20-Day simple moving average trend was calculated using the price of the 20-day simple moving average on the result date and the price of moving 20 working days before that date. This calculation helped to understand the trend of the fluctuation in the stock's price during a designated time, providing insights into the stock's performance and future movements. Subsequently, for each quarter, the next three months' prices were iterated. Stocks were bought on the result date and sold if the price of the stock dropped by 5% or the current price of the stock is at or below the 20-day simple moving average. A label of 1 was assigned if the profit was booked, and a label of 0 was assigned if the position was exited on loss. This process resulted in a dataset that could be classified using a binary classification model. The data was now ready for analysis, and the binary classification model could be used to predict the probability of booking a profit or incurring a loss derived from the historical data of equity prices.

The resulting dataset was then classified using a binary classification model, enabling predictions of future stock performance. The final dataset obtained after the preprocessing stage can now be used to conduct further analysis, generate insights, and inform investment decisions. Mathematically, the t-Day moving average can be determined with the help of following equation:

$$SMA_t = \frac{1}{t}\sum_{i=1}^{t} P_i \tag{1}$$

Where 'SMA_t' refers to the t-Day simple moving average, 'P_i' represents the closing price of the stock on the previous i^{th} day. For example, if we want to calculate the 20-Day SMA of a stock's closing price over a period of 20 trading days, we sum up the closing prices of the stock over the 20-day period and then divide the sum by 20. The simple moving average can be plotted on a graph alongside the stock's price, providing insights into the stock's performance over a specified period. The utilization of the simple moving average enables the identification of trends, support and resistance levels, as well as the potential emergence of buy or sell signals. To calculate the stop loss, we used the following formula:

$$SL = \frac{19}{20}[\alpha * cP + \frac{\beta}{t}(\sum_{k=1}^{t} pL_k) + \frac{\gamma}{t}(\sum_{j=1}^{t} pH_j)] \tag{2}$$

Where 'SL' refers to the stop loss, 'α', 'β', and 'γ' are smoothing constants. The values of these constants, which are 0.41, 0.34, and 0.25 respectively, were determined by evaluating over 2000 combinations of values. 'cP' represents the stock's closing price on the present day while 'pL_k' and 'pH_k' represent the low and high prices of the stock on the previous kth day, respectively.

3.3. Proposed Model

A binary classification neural network model was used to train a dataset that contained normalized financial parameters along with a corresponding label that indicated a buy signal. The purpose of this model was to classify whether a given financial scenario would result in a buy signal or not.

The neural network model used in this approach is a binary classification model which tries to learn hidden patterns in the data and those patterns can be used to predict the result on the given input values. In this case, the model underwent training using a dataset. of financial parameters and their corresponding labels. The success of this approach was measured by the accuracy of the model, which was found to be 62.90%. This signifies that the model achieved a 62.90% accuracy rate in accurately predicting the financial scenarios present in the dataset. Overall, this binary classification neural network model proved to be effective in predicting buy signals based on financial parameters. With further refinement and tuning, it has the potential to become an even more accurate tool for financial analysis and decision-making. The proposed is divided into following units as shown in fig 2 which are:

3.3.1. Artificial Neural Network Model

We have used a foundational artificial neural network (ANN) architecture where data flows in one way, from input nodes through hidden layers to output nodes. It excels in classification tasks and pattern recognition, utilizing weights and biases to learn and make predictions without feedback loops.

After collecting and pre-processing the data, the authors tested various machine learning models, including the random forest classifier, logistic classifier, and support vector machine (SVM), to analyse the resulting dataset. However, despite these efforts, these models failed to produce satisfactory results. To address this issue, the team decided to employ a binary classification neural network model to train the data. This model incorporated all the normalized financial parameters, along with a label that indicated a buy signal. The neural network model proved to be successful, achieving an accuracy of 62.90%, outperforming the previous models tested.

The binary classification neural network model serves as an exemplification of the machine learning model that harnesses artificial neural networks to acquire knowledge and generate forecasts. This model works by taking in a set of inputs (in this case, the financial parameters) and processing them through a series of layers to produce an output (in this case, the buy signal label). The neural network model used in this research incorporated a range of advanced techniques, consisting of batch normalization, dropout regularization, and early stopping. Dropout regularization aids in mitigating overfitting concerns by selectively deactivating certain nodes within the neural network during the training phase. Batch normalization helps improve the stability of the model during training, while early stopping is a technique employed to address overfitting by halting the training process when the validation error no longer exhibits improvement, thereby preventing the model from excessively fitting the training data. Overall, the success of the binary classification neural network model in this research demonstrates the potential of using advanced machine learning techniques for financial analysis. With these results, investors can make better-informed decisions when considering the quarterly results of a company. This research highlights the potential for using neural networks for future financial analysis and opens new avenues for research in this field.

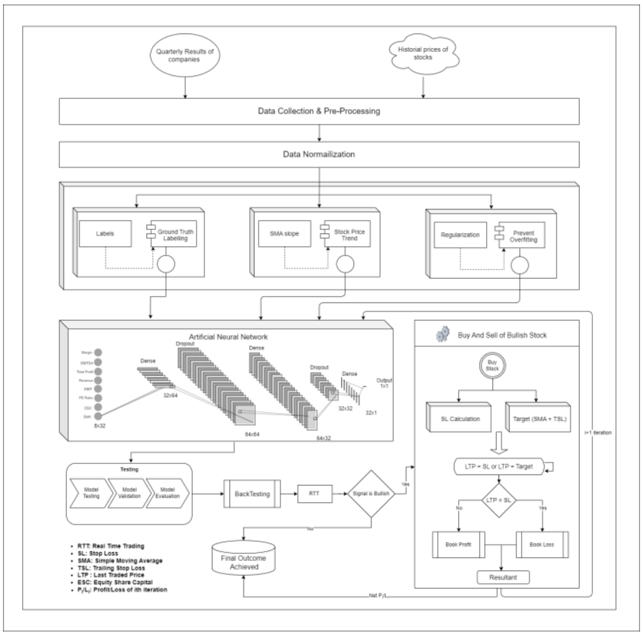


Fig. 1. Data-driven Stock Market Prediction Framework

3.3.2. Data Extraction and Creation Unit

To create a dataset with percentage change in financial parameters, the following steps were taken:

1. Collected raw financial data from relevant sources such as the NSE website and the quarterly results data from moneycontrol website.
2. Calculate the change in each financial parameter for each company in the dataset. This has been done by subtracting the current period value from the previous period value and dividing by the current period value. For example, to calculate the change in revenue from Q1 FY 20-21 to Q2 FY 20-21, subtract the revenue value for Q1 FY 20-21 from the revenue value for Q2 FY 20-21, then divide by the revenue value for Q1 FY 20-21. The following equations have been used to calculate change.

$$P_{change} = \frac{Cv\ -\ Pv}{Pv} \tag{3}$$

The notation 'Cv' and 'Pv' refers to the value of a specific parameter in the current quarter and the previous quarter, respectively. The parameter set denoted by 'P' encompasses a range of important financial metrics such as Margin, EBITDA, revenue, profit, equity share capital and EBIT.

3. The SMA trend was found by calculating the slope of the SMA. To calculate the slope the following formula has been used.

$$SMA\ slope\ = \frac{P_{cur}\ \ -\ \ P_{cur-20}}{20} \tag{4}$$

Where ‘P_{cur}’ and ‘P_{cur-20}’ refer to the price of the SMA20 on the current day and twenty days prior to the current day, respectively.

3.3.3. Classifying stock price using Neural Networks

In this unit, a binary classification neural network model has been defined using the deep learning libraries of python. The model comprises the following layers: two fully connected dense layers incorporating ReLU in the capacity of the activation function and employing a sigmoid activation function for the output layer.

Linear Unit (ReLU) as its activation function, which is a frequently utilized component in deep learning models. ReLU activation function helps to introduce non-linearity in the model and make it more expressive. After the initial Dense layer, a Dropout layer is incorporated with a dropout rate of 0.5. The Dropout layer is a regularization technique used in neural networks to prevent overfitting. The dropout drops out some percentage of the networks formed, which is useful to prevent the model from memorizing the training data and improves its generalization performance. The second Dense layer has 32 units with ReLU activation function. This layer also incorporated a Dropout layer after the dense layer with a rate of 0.5. In the end, the output layer comprises a solitary neuron that utilizes the sigmoid (σ) as its activation function. The sigmoid activation function is used for binary classification tasks, where the output is a probability value within the range of 0 to 1, indicating the probability of the input being associated with a specific class.

The model is assembled using the binary cross entropy loss function. The optimizer used in this model is Adam, which is an efficient optimization algorithm that automatically customizes the learning rate (lr) during training. The performance of the model is evaluated using the accuracy metric. Overall, this model architecture is a simple yet effective neural network design for binary classification tasks. It includes regularization techniques to prevent overfitting and an efficient optimizer to improve training efficiency. With appropriate tuning, this model architecture can be applied to various binary classification tasks in the financial domain.

ALGORITHM 1: To find the label for each record

```
function FIND_LABEL(qtr_result_date, buy_price):
    1.  label = None
    2.  stoploss_price=CALCULATE_STOPLOSS(buy_price)
    3.  FOR day in range(qtr_result_date, qtr_result_date + 90):
    4.          cur_price = PRICE_ON_DATE(day, symbol)
    5.          sma_price = 20SMA_PRICE(day, symbol)
    6.          if cur_price <= stoploss_price :
    7.                  SET_LABEL(label, 0)
    8.                  break
    9.          else:
    10.                 SET_LABEL(label, 1)
    11. END FOR
    12. return label
end function
```

ALGORITHM 2: Stock price prediction using neural networks

```
Function SP_USING_NEURAL_NETWORK(qtr_res, qtr_result_date):
    1.  norm_res ← []
    2.  prev_res ← None
    3.  for i in range(len(qtr_res)):
    4.        if i == 0:
    5.              DO NOTHING
    6.        else:
    7.              change = ((qtr_res[i] - prev_res) / prev_res) * 100
    8.              norm_res.append(change)
    9.        prev_res = qtr_res[i]
    10. signal=NEURAL_NETWORK_MODEL(norm_res)
    11. return signal
end function
```

3.4. Evaluation Unit

This unit involves using the results of neural networks to make predictions for upcoming trends in the equity market. Drawing upon the evidence from classification given by the neural networks, investors can make informed decisions on whether to buy or avoid certain stocks. If the neural network classifies the given input as a 1 indicates that the stock is poised to experience a bullish trend, and investors may consider buying it. Conversely, if the neural network classifies the input as a 0, it indicates that the stock is poised to experience a bearish trend, and investors should avoid buying it. This approach can be useful for investors who want to make data-driven choices and mitigate potential risks involved in equity market investments. However, it is important to note that there may be limitations and uncertainties involved in using this type of prediction model, and other factors should also be considered before making investment decisions.

ALGORITHM 3: Evaluation unit

```
function PREDICTION(qtr_res, qtr_res_date):
    1.  signal= SP_USING_NEURAL_NETWORK(qtr_res, qtr_res_date)
    2.  if signal == 1:
    3.          buy_price = PRICE_ON_DATE(qtr_res_date)
    4.  for day in range(qtr_res_date, qtr_res_date + 90):
    5.          cur_price = PRICE_ON_DATE(day)
    6.          sma_price = 20SMA_ON_DATE(day)
    7.          change = (cur_price - buy_price) / buy_price
    8.   if change <= -0.05 or sma_price == cur_price:
    9.  SELL()
    10. else:
    11. return
end function
```

4. Experimental Setup

The experiment involved a retrospective study of quarterly financial data from moneycontrol.com and equity prices of 1000 firms registered on the NSE. The data was collected over a 3-year period to analyze the correlation between the financial condition of a company and its equity share prices. The study aimed to develop an effective forecasting model for investors by examining key financial indicators such as margin, profit, EBITDA, revenue, EBIT, PE ratio, and Equity Share Capital. Overall, the experiment setup provided a comprehensive dataset for the study and enabled the development of valuable insights for investors in the stock market.

4.1 Dataset Description

This dataset contains quarterly financial data of 1,000 firms included within the roster of securities on the NSE over a three-year period. It includes margin change, profit change, EBITDA change, revenue change, EBIT change, PE ratio percentage change, and Equity Share Capital change with to the previous quarter, as well as the 20 SMA trend, which is defined as the slope between the 20-day simple moving average (SMA) value on the result date and the 20-day SMA value on the trading day 20 days prior. The final dataset contains over 12,000 records and is suitable for analysis and modelling of financial performance in the Indian stock market.

The following table shows a sample of rows from the final dataset.

Table 1. Dataset Description

SYMBOL & QUARTER	MA TREND	MARGIN CHANGE	EBITDA CHANGE	REVENUE CHANGE	TOTAL PROFIT CHANGE	EQUITY SHARE CAPITAL CHANGE	EBIT CHANGE	PE RATIO	LABEL
AARTIDRUGS Q1 FY 21-22	-0.50	-0.18	-0.02	0.13	-0.06	-0.06	-0.01	137.2	0

AARTIDRUGS Q2 FY 21-22	0.25	-0.10	-0.10	0.00	-0.15	-0.14	-0.12	135.3	0
BATAINDIA Q1 FY 21-22	0.58	1.28	1.61	-1.21	1.42	1.42	1.93	-307	1
BATAINDIA Q2 FY 21-22	11.43	4.10	2.35	0.57	2.87	2.87	1.96	704.2	0
CENTURYPLY Q1 FY 21-22	0.77	-0.58	-1.57	-0.63	-1.80	-1.77	-1.50	302.9	1
CENTURYPLY Q2 FY 21-22	6.16	0.47	0.70	0.44	0.69	0.68	0.68	152.3	0
EASEMYTRIP Q1 FY 21-22	1.46	-1.11	-5.49	-2.07	-0.97	-0.97	-1.10	332.4	1
EASEMYTRIP Q2 FY 21-22	-4.22	0.44	0.76	0.57	0.43	0.43	0.43	201.8	1
ITI Q1 FY 21-22	-0.06	1.56	4.10	-4.52	3.29	3.30	6.48	-132	0
ITI Q2 FY 21-22	0.02	-2.98	-1.59	0.35	-0.58	-0.57	-2.96	-196	0
UBL Q1 FY 21-22	2.79	-2.60	-3.96	-0.38	-2.15	-2.14	-3.55	1,233	1
UBL Q2 FY 21-22	3.20	0.53	0.63	0.22	0.61	0.62	0.59	557	0

4.2 Experiment Testbed

In this research, a computer system consisting of Intel i5 10th generation processor, 8GB RAM, and a 4GB NVIDIA graphics card was used. The researchers chose Python as the primary programming language due to its ability to efficiently perform complex operations and streamline the research process. The Jupyter notebook was utilized as the primary Integrated Development Environment (IDE), providing an interactive and user-friendly interface for coding and analysis. Furthermore, various standard Python libraries such as Numpy, Pandas, MatplotLib, and Beautifulsoup were used to perform data manipulation, analysis, and visualization. These libraries are widely used and provide a range of tools and functions to enable efficient and accurate data processing. Overall, the combination of a powerful computer system, advanced programming language, and essential libraries allowed the researchers to perform complex analyses and derive meaningful insights from the data.

5. Results and performance analysis

The study examined the potential profitability of using quarterly results to predict stock prices. To achieve this, the research utilized a systematic approach that involved analyzing the data of approximately 1000 firms. The model was then iterated over the last 3 years, and a buy signal was initiated when the model signalled a buy. The stock was sold either when the stock price dropped by 5% from the buy price or when the 20-day SMA price became either greater or equal to the equity last traded price.

The results of the study were promising, with an average profit of 142% in the last 3 years and 34.7% profit on yearly basis. This finding highlights the potential value of using quarterly results to forecast the equity prices and underscores the significance of conducting financial analysis to make well-informed investment decisions. Furthermore, the study highlights the importance of considering individual companies' financial indicators when analyzing their quarterly results. By examining key financial indicators such as margin, profit, EBITDA, revenue, EBIT, PE ratio, and Equity Share Capital, investors can make more informed decisions when investing in the equity market. Overall, the study offers valuable perspectives on the progress of effective forecasting models for investors, which could help them make more profitable investment decisions.

As the model employed a binary classification approach, a confusion matrix was utilized to appraise the accuracy of the results. This allowed us to examine the model's performance and analyze the outcomes. Upon analyzing the confusion matrix, the following results were obtained:

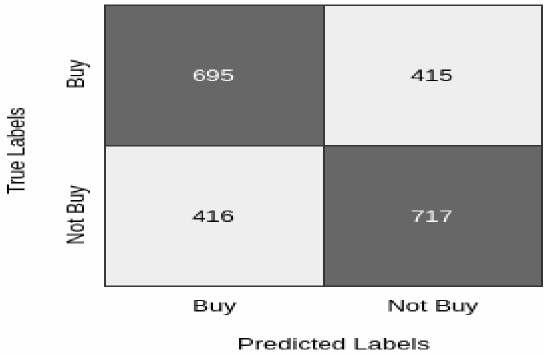


Fig. 2 Confusion Matrix of the labels predicted by the model.

As shown in Fig. 2, the accuracy can be determined, resulting in a value of 62.90%. This result is highly promising and could prove to be an invaluable asset for investors. Based on the results presented in the following table, we achieved an impressive average profit of 142% over the span of three years. The highest net profit recorded was 567.11%, while the lowest was a loss of 11.35%. These figures indicate a very promising trend, making them valuable tools for investors to use when making decisions in the equity market. The following table shows profit and loss data for a few companies coupled with the corresponding accuracy offered by the proposed neural networks model.

Table 2. Results of the proposed model on various stocks

SYMBOL	NET PROFIT (%)	ACCURACY (%)
TANLA	567.11	43.75
ADANIGREEN	563,17	86.67
REDINGTON	255.55	70.59
KAJARIACER	170.47	56.25
ADANIPORTS	118.00	66.67
UTIAMC	58.80	57.14
3IINFOLTD	18.55	75.00
KRSNAA	-7.74	50.00
DODLA	-11.35	50.00
BHARTIARTL	45.00	50.00

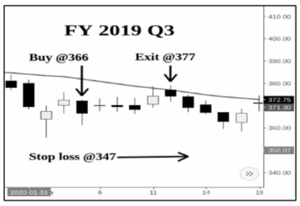
Our case study focuses on ADANI PORTS, a national stock exchange-listed company. The proposed model was utilized for making market decisions during back testing. The study analyzes profit and loss data in all quarters in FY 19-20 and FY 20-21, spanning approximately 2 years. The results are truly promising, as an initial investment of 100,000 yielded a return of 157,450 within this time frame.

The table provides a comprehensive overview of the investment performance and outcomes of a model over several quarters during the fiscal years 2019-2020 and 2020-2021. Each row in the table corresponds to a specific quarter and contains relevant information in different columns. The "Quarter" column specifies the fiscal quarter being analyzed. The "Model Signal" column indicates whether the market sentiment during that quarter was bearish or bullish. The "Buy Price" column shows the price at which investments were made during the respective quarters, while the "Exit Price" column displays the price at which the investments were sold or exited. The "Price Change" column indicates the percentage gain/loss in price from the purchase price to the exit price, giving insight into the investment's performance. The "Invested Amount" column denotes the initial amount invested during each quarter. The "Profit/Loss" column mirrors the net profit or loss generated from the allocated funds during the specific quarter. The "Total Amount" column provides an overview of the cumulative amount, including the initial investment amount and any profits or losses. By examining the table, it is possible to track the investment performance over time, observe the profitability of each quarter, and evaluate the model's ability to generate returns during both bearish and bullish market conditions. This information is valuable in assessing the model's effectiveness and understanding its performance trends throughout the fiscal years 2019-2020 and 2020-2021.

Through the application of the proposed model, ADANI PORTS demonstrated exceptional profitability, generating a remarkable 57.5% profit within a span of 2 years. These impressive results underscore the effectiveness of the model in predicting profitable market decisions for listed companies. In Fig 3. to Fig. 8 the candlestick charts of each quarter in FY 19-20 and FY 20-21 is shown with the buy price, stop loss and exit price marked.

Table 3. Performance of Adani Ports

SYMBOL	NET PROFIT (%)	ACCURACY (%)
TANLA	567.11	43.75
ADANIGREEN	563,17	86.67
REDINGTON	255.55	70.59
KAJARIACER	170.47	56.25
ADANIPORTS	118.00	66.67
UTIAMC	58.80	57.14
3IINFOLTD	18.55	75.00
KRSNAA	-7.74	50.00
DODLA	-11.35	50.00
BHARTIARTL	45.00	50.00



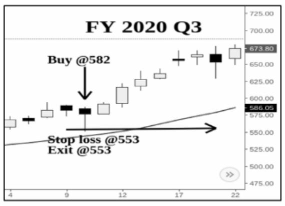


Fig. 3 Adani ports Q3 FY 19-20

Fig. 6 Adani ports Q2 FY 20-21

Fig. 4 Adani ports Q4 FY 19-20

Fig. 7 Adani ports Q3 FY 20-21

Fig. 5 Adani ports Q1 FY 20-21

Fig. 8 Adani ports Q4 FY 20-21

5 Conclusion And Future Works

This research work provides valuable insights into the impact of quarterly results on stock prices, highlighting the importance of analyzing financial data in stock market prediction. The proposed systematic approach offers an effective means of analyzing the relationship between a financial status of a business and its equity share prices by examining key financial indicators, such as margin, profit, EBITDA, revenue, EBIT, PE ratio, and Equity Share Capital. The study reveals that analyzing stocks based on their quarterly results can be an excellent tool for predicting stock prices. Moreover, the findings of the research indicate that the proposed approach outperforms the random walk model, which is often used as a benchmark in the equity market prediction studies.

The artificial neural network model used in the study could be further improved by training it on a larger dataset, thus enabling investors to make more informed decisions in the equity market. In addition, the research holds the possibility to inspire other researchers to explore the prediction of quarterly results using stock fundamentals. The systematic approach presented in this study can serve as a useful guide for other researchers who seek to scrutinize the effect of quarterly results on equity prices. Overall, the study offers a systematic approach for analyzing the influence of financial data on equity prices and emphasizes the crucial role of constructing robust forecasting models to empower investors. The findings of this study can be useful for investors, analysts, and researchers who want to make informed decisions and predictions about equity prices.

Prospective analysis in this domain has the potential to search into various avenues, offering more opportunities for further exploration and enhancement. First, the artificial neural network model used in the study could benefit from training on a larger and more diverse dataset. This expanded dataset would enable the model to capture a broader range of patterns and trends, thereby enhancing its predictive capabilities in the equity market. Additionally, further research can be conducted to investigate the prediction of quarterly results using other stock fundamentals beyond the ones considered in this study. Exploring additional financial indicators or combining multiple indicators could provide deeper insights into the relationship between financial data and equity prices. This expanded analysis would contribute to a more thorough comprehension of the factors influencing equity market dynamics.

References

[1] P. Yu and X. Yan, “Stock price prediction based on deep neural networks,” Neural Computing and Applications, vol. 32, no. 6. Springer Science and Business Media LLC, pp. 1609–1628, Apr. 17, 2019. doi: 10.1007/s00521-019-04212-x.

[2] Y. Huang, L. F. Capretz and D. Ho, "Neural Network Models for Stock Selection Based on Fundamental Analysis," 2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE), Edmonton, AB, Canada, 2019, pp. 1-4, doi: 10.1109/CCECE.2019.8861550.

[3] O. Bustos and A. Pomares-Quimbaya, “Stock market movement forecast: A Systematic review,” Expert Systems with Applications, vol. 156. Elsevier BV, p. 113464, Oct. 2020. doi: 10.1016/j.eswa.2020.113464.

[4] Z. Jin, Y. Yang, and Y. Liu, “Stock closing price prediction based on sentiment analysis and LSTM,” Neural Computing and Applications, vol. 32, no. 13. Springer Science and Business Media LLC, pp. 9713–9729, Sep. 19, 2019. doi: 10.1007/s00521-019-04504-2.

[5] I. K. Nti, A. F. Adekoya, and B. A. Weyori, “A systematic review of fundamental and technical analysis of stock market predictions,” Artificial Intelligence Review, vol. 53, no. 4. Springer Science and Business Media LLC, pp. 3007–3057, Aug. 20, 2019. doi: 10.1007/s10462-019-09754-z.

[6] W. Khan, M. A. Ghazanfar, M. A. Azam, A. Karami, K. H. Alyoubi, and A. S. Alfakeeh, “Stock market prediction using machine learning classifiers and social media, news,” Journal of Ambient Intelligence and Humanized Computing, vol. 13, no. 7. Springer Science and Business Media LLC, pp. 3433–3456, Mar. 14, 2020. doi: 10.1007/s12652-020-01839-w.

[7] A. Picasso, S. Merello, Y. Ma, L. Oneto, and E. Cambria, “Technical analysis and sentiment embeddings for market trend prediction,” Expert Systems with Applications, vol. 135. Elsevier BV, pp. 60–70, Nov. 2019. doi: 10.1016/j.eswa.2019.06.014.

[8] X. Li, P. Wu, and W. Wang, “Incorporating stock prices and news sentiments for stock market prediction: A case of Hong Kong,” Information Processing & Management, vol. 57, no. 5. Elsevier BV, p. 102212, Sep. 2020. doi: 10.1016/j.ipm.2020.102212.

[9] A. Moghar and M. Hamiche, “Stock Market Prediction Using LSTM Recurrent Neural Network,” Procedia Computer Science, vol. 170. Elsevier BV, pp. 1168–1173, 2020. doi: 10.1016/j.procs.2020.03.049.

[10] A. Yadav, C. K. Jha, and A. Sharan, “Optimizing LSTM for time series prediction in Indian stock market,” Procedia Computer Science, vol. 167. Elsevier BV, pp. 2091–2100, 2020. doi: 10.1016/j.procs.2020.03.257.

[11] M. Vijh, D. Chandola, V. A. Tikkiwal, and A. Kumar, “Stock Closing Price Prediction using Machine Learning Techniques,” Procedia Computer Science, vol. 167. Elsevier BV, pp. 599–606, 2020. doi: 10.1016/j.procs.2020.03.326.

[12] A. H. Bukhari, M. A. Z. Raja, M. Sulaiman, S. Islam, M. Shoaib, and P. Kumam, “Fractional Neuro-Sequential ARFIMA-LSTM for Financial Market Forecasting,” IEEE Access, vol. 8. Institute of Electrical and Electronics Engineers (IEEE), pp. 71326–71338, 2020. doi: 10.1109/access.2020.2985763.

[13] M. Nabipour, P. Nayyeri, H. Jabani, S. S., and A. Mosavi, “Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data; a Comparative Analysis,” IEEE Access, vol. 8. Institute of Electrical and Electronics Engineers (IEEE), pp. 150199–150212, 2020. doi: 10.1109/access.2020.3015966.

[14] K. Zhang, G. Zhong, J. Dong, S. Wang, and Y. Wang, “Stock Market Prediction Based on Generative Adversarial Network,” Procedia Computer Science, vol. 147. Elsevier BV, pp. 400–406, 2019. doi: 10.1016/j.procs.2019.01.256.

[15] E. Hoseinzade and S. Haratizadeh, “CNNpred: CNN-based stock market prediction using a diverse set of variables,” Expert Systems with Applications, vol. 129. Elsevier BV, pp. 273–285, Sep. 2019. doi: 10.1016/j.eswa.2019.03.029.

[16] V. Tyagi, A. Kumar, and S. Das, “Sentiment Analysis on Twitter Data Using Deep Learning Approach,” 2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN). IEEE, Dec. 18, 2020. doi: 10.1109/icacccn51052.2020.9362853.

[17] P. R. Charkha, “Stock Price Prediction and Trend Prediction Using Neural Networks,” 2008 First International Conference on Emerging Trends in Engineering and Technology. IEEE, 2008. doi: 10.1109/icetet.2008.223.

[18] P. Gao, R. Zhang, and X. Yang, “The Application of Stock Index Price Prediction with Neural Network,” Mathematical and Computational Applications, vol. 25, no. 3. MDPI AG, p. 53, Aug. 18, 2020. doi: 10.3390/mca25030053.

[19] T. Kimoto, K. Asakawa, M. Yoda, and M. Takeoka, “Stock market prediction system with modular neural networks,” 1990 IJCNN International Joint Conference on Neural Networks. IEEE, 1990. doi: 10.1109/ijcnn.1990.137535.

[20] A. H. Moghaddam, M. H. Moghaddam, and M. Esfandyari, “Stock market index prediction using artificial neural network,” Journal of Economics, Finance and Administrative Science, vol. 21, no. 41. Elsevier BV, pp. 89–93, Dec. 2016. doi: 10.1016/j.jefas.2016.07.002.

[21] M. Nikou, G. Mansourfar, and J. Bagherzadeh, “Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms,” Intelligent Systems in Accounting, Finance and Management, vol. 26, no. 4. Wiley, pp. 164–174, Oct. 2019. doi: 10.1002/isaf.1459.

[22] X. Pang, Y. Zhou, P. Wang, W. Lin, and V. Chang, “An innovative neural network approach for stock market prediction,” The Journal of Supercomputing, vol. 76, no. 3. Springer Science and Business Media LLC, pp. 2098–2118, Jan. 12, 2018. doi: 10.1007/s11227-017-2228-y.

[23] W. Jiang, “Applications of deep learning in stock market

prediction: Recent progress," Expert Systems with Applications, vol. 184. Elsevier BV, p. 115537, Dec. 2021. doi: 10.1016/j.eswa.2021.115537.

[24] W. Long, Z. Lu, and L. Cui, "Deep learning-based feature engineering for stock price movement prediction," Knowledge-Based Systems, vol. 164. Elsevier BV, pp. 163–173, Jan. 2019. doi: 10.1016/j.knosys.2018.10.034.

[25] K. Khare, O. Darekar, P. Gupta, and V. Z. Attar, "Short term stock price prediction using deep learning," 2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT). IEEE, May 2017. doi: 10.1109/rteict.2017.8256643.

[26] G. Li, A. Zhang, Q. Zhang, D. Wu and C. Zhan, "Pearson Correlation Coefficient-Based Performance Enhancement of Broad Learning System for Stock Price Prediction," in IEEE Transactions on Circuits and Systems II: Express Briefs, vol. 69, no. 5, pp. 2413-2417, May 2022, doi: 10.1109/TCSII.2022.3160266.

[27] Y. Zhao et al., "Stock Movement Prediction Based on Bi-Typed Hybrid-Relational Market Knowledge Graph Via Dual Attention Networks," in IEEE Transactions on Knowledge and Data Engineering, 2022, doi: 10.1109/TKDE.2022.3220520.

[28] H. Wang, T. Wang, S. Li and S. Guan, "HATR-I: Hierarchical Adaptive Temporal Relational Interaction for Stock Trend Prediction," in IEEE Transactions on Knowledge and Data Engineering, 2022, doi: 10.1109/TKDE.2022.3188320.