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The Analysis of The Daily Return Percentage as An Alternative To The Closing Price Of The Stock Using The Ensemble Model

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Abstract—In stock exchanges, buyers and sellers meet to trade shares in public companies. Stock exchanges encourage investment. Raising capital enables companies to grow, expand, and create jobs in the economy. These investments are critical enablers of trade, economic growth, and prosperity. Data preprocessing and cleaning are integral to machine learning research and studies. This paper highlights the common mistakes present among the various models for stock price prediction, and it also offers the solution to the problem and a procedure to prepare the data, which any model can use as input. Our objective is to comprehend various models and studies that have been normalizing the price data of the stock, which causes the price to be fixed in each range, which is not valid in real-world scenarios; hence, such models will produce inaccurate predictions over a period. To solve this problem, this paper discusses Daily Return % as an alternative to close prices. To the best of our knowledge, this is the first paper discussing the issue of scaling the parameter known as the price. To achieve this, we use exploratory data analysis techniques and data visualization that focus on modeling and knowledge discovery for predictive rather than just descriptive processing. It assures good data quality and consistency. This study examines the issue of data cleaning and pinpoints a possible inaccuracy in a TATA POWER dataset. A quick summary of the current data-cleaning approaches and a survey and assessment of the many perspectives on data cleaning are provided.
Keywords—Analysis of the stock, Ensemble Learning, Regression

INTRODUCTION

As the world is heading towards the AI revolution, all aspects of our daily lives are slowly being managed by such data-consuming models [27][28]. In the same direction, much work has been done in AI trading and stock price prediction [29][30][31] while using various machine learning models that feed upon the years of data stored by the stock exchange and by using [32][33] various algorithms, produce predictions for the future. This paper will discuss all the steps involved in data pre-processing and define a method [34][35] to prepare a dataset for training any machine learning model. We'll also focus on the price data's improper scaling (Min-Max Scaling) [36][37]. For demonstration purposes, we'll be using the archived data of Tata Power Company from NSE archives. The company is listed on the National Stock Exchange of India Limited and BSE Limited (NSE)[38][39][40].

The paper uses the data from NSE archives for TATA POWER from 1ST January 2003 to 31 December 2022 [41][42].

Further, we performed data analysis and cleansing on Jupyter Notebook, such as analyzing the data on missing values, attribute duplication, removing irrelevant columns, adding relevant columns, plotting the graph, and performing Exploratory Data Analysis [43][44]. Data can provide in-depth information about users, customer base, and markets [45][46]. Data can help companies learn about new product opportunities, market segments, industry verticals, and more when combined with analytical tools [7]. The issue isn't a shortage of data; instead, it needs more clarity regarding how the data should be precisely examined and applied [9].

MATERIALS AND METHODS

Analyzing stock market data has been done using machine learning methods like decision trees [2], support vector machines [14], and neural networks [29]. The data analysis by predicting the value is possible because of the ensemble model XGBoost and AdaBoost. Both models are already separate Ensemble models in themselves. Examining and cleaning stock market data has been the subject of numerous research studies. These articles cover a variety of broad topics, some of which are listed below:

1. Data preparation: Techniques for preparing stock market data, such as handling missing values, removing outliers, and normalizing the data, have been the subject of numerous articles [17][18]. The last closing price of the shares of TATA Power is collected (2003-2022) from the National Stock Exchange. To ensure the model goes well with the other data (stock), the analysis of the stock of ITC is also done.
2. Feature Extraction—Researchers have created several techniques for separating relevant aspects from stock market data, including sentiment analysis, technical indicators, and fundamental information [16]. The fundamental Exploratory Analysis Techniques were employed to remove the outliers using the quartiles. The closing price has the highest impact on the decision to buy or sell the stock. The impact analysis is carried out by plotting the correlation matrices [47][48]. Open, High, Low, and % Return are the shortlisted parameters.
3. Model Selection: Much research has been done on selecting the best model (or set of models) to use in making stock market predictions [15], including both conventional statistical models and machine learning techniques [16]. The single standalone model is not sufficient to deliver the higher accuracy. The hybrid model using the stacking technique is used. Initial weights are equally distributed, and after the iteration, the weights are calculated to fit the model.
4. Evaluation: Several approaches, including train-test splits, cross-validation, and back testing, have been put forth by researchers to assess the effectiveness of stock market prediction models [19]. The results are
5. Numerous studies have been done on using stock market data analysis and cleaning techniques in various fields, including algorithmic trading, risk management, and portfolio optimization [17][18].

Almost all the studies involving price prediction and model training followed a similar pattern in data normalization [23]. Few models [12] directly used the price of the stock as an input to train the model, whereas others [21][18] performed min-max scaling over the price. Scaling prices is a common problem seen with most models and articles. Scaling is done in the first place to reduce any given numerical data into a small range, usually from zero to one. Scaling helps reduce the processing while training the models; now, the system must deal with a smaller range of data [4]. But the problem with scaling the price data is that there might be a fixed lower limit (zero) but there cannot be a fixed upper limit in terms of price as it will change with the company's growth. Models that are scaling the price data are fixing an upper limit to the price that cannot be crossed [22][26]; hence the models are bound to produce inaccurate outputs in the long term.

ARCHITECTURE

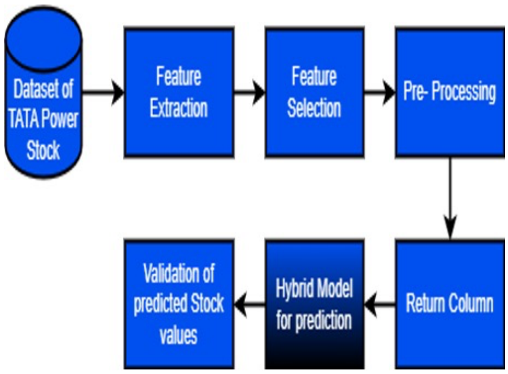

Fig. 1. Architecture of the Return Column Prediction Model

EMPIRICAL RESULTS

When data is available, it needs pre-processing before it can be fed into a machine-learning model. The meaning of the output depends on the pre-processing of the data. To share the understanding of knowledge concepts and techniques, we will take the example of the TATA POWER and ITC datasets available in NSE archives and try to extract as much knowledge as possible from the dataset using EDA.

```python
#Importing Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(style="darkgrid")
```

Fig. 2. Importing Libraries NumPy, Pandas, matplotlib, and seaborn..

The “Open” Column represents the opening price for shares that day. “Close” represents the price shares ended for the day. “Low” represents the lowest price for the day. “High” represents the highest price shares reached that day. “Last” represents the price at which the last transaction for a share went through. “Return” represents the total profit or loss in the stock price.

Stock Prices dataset	Feature	Training Set	Testing Set
Tata Power Stock Price	‘Open’ ‘High’ ‘Low’ ‘Close’ ‘%Return’	1st Jan 2003 to 1st Jan 2019	1st Jan 2019 to 31st Dec 2022
ITC Stock Price	‘Open’ ‘High’ ‘Low’ ‘Close’ ‘%Return’	16th Nov 2005 to 28th Jun 2019	1st Jul 2019 to 14th Nov 2022

Fig. 3. Description of Dataset.

This graph represents that there was a split in the price of the stocks because of which there is a sudden drop in the graph in the year 2011.

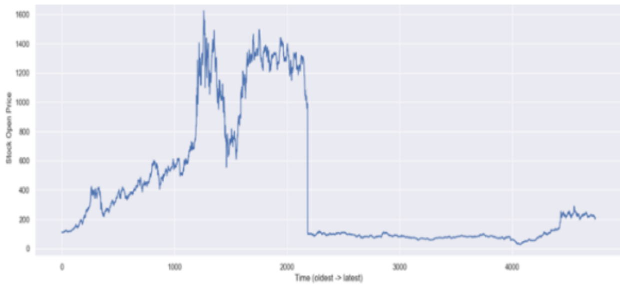

Fig. 4. Average Price Plot Before Preprocessing.

Figure 5 gives us the description of the Column and their data types:

1. Data has only float, integer, and object values.
2. No variable column has null/missing values.

```
RangeIndex: 4738 entries, 0 to 4737
Data columns (total 15 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Symbol                  4738 non-null   object
 1   Series                  4738 non-null   object
 2   Date                    4738 non-null   object
 3   Prev Close              4738 non-null   float64
 4   Open Price              4738 non-null   float64
 5   High Price              4738 non-null   float64
 6   Low Price               4738 non-null   float64
 7   Last Price              4738 non-null   float64
 8   Close Price             4738 non-null   float64
 9   Average Price           4738 non-null   float64
 10  Total Traded Quantity   4738 non-null   int64
 11  Turnover                4738 non-null   float64
 12  No. of Trades           4738 non-null   object
 13  Deliverable Qty         4738 non-null   int64
 14  % Dly Qt to Traded Qty  4738 non-null   object
dtypes: float64(8), int64(2), object(5)
memory usage: 555.4+ KB
```

Fig. 5. Analyzing the Data Types in Data Before Pre-processing

Converting the object values into numbers so that algorithms can readily process them and removing the extra Symbol column as it contains single-category data. In addition, while analyzing the data, we observed that on 11 Sept 2011, Tata Power Stock split in the ratio of 1:10, dividing all the prices before that by ten and multiplying the traded quantity and deliverable quantity by 10 to maintain the evenness in data. Also, we added a new column, Return%, to show the total profit or loss in the stock price.

The following are the steps performed before Preprocessing:

1. Replacing the Missing Values of the number of trades with Column Avg.
2. Converting object values into float
3. Replacing deliverable % on missing values with 100 as in bulk Order delivery percent is 100.
4. Converting Dates into the numeric format.
5. Removing the symbol column as it contains single-category data.
6. Turning the categorical data into numbers (Series)
7. Adding a Return column.

We can observe that a new column, “Return%”, has been included, and the column “Symbol” has been removed. “Return%” can be used in the normalization and training of the model as for all stock exchanges, there’s a fixed range in which the daily return can vary, which could be used to scale the column.

	Series	Date	Prev Close	Open Price	High Price	Low Price	Last Price	Close Price	Average Price	Total Traded Quantity	Turnover	No. of Trades	Deliverable Qty	% Dly Qt to Traded Qty	%Return
0	True	01 01 03	11.170	11.230	11.230	11.105	11.165	11.145	11.158	1053010.0	11749225.30	52248.0	350010.0	33.24	-0.223814
1	True	02 01 03	11.145	11.120	11.195	11.015	11.050	11.045	11.106	1123080.0	12472530.85	52248.0	616530.0	54.90	-0.897263
2	True	03 01 03	11.045	11.115	11.190	10.905	10.925	10.925	11.003	935820.0	10296827.00	52248.0	541180.0	57.83	-1.086464
3	True	06 01 03	10.925	10.960	11.050	10.745	10.765	10.780	10.898	1249510.0	13616753.80	52248.0	633160.0	50.67	-1.327231
4	True	07 01 03	10.780	10.980	10.980	10.620	10.655	10.655	10.702	1075870.0	11514225.70	52248.0	697940.0	64.87	-1.159555

Fig. 6. Description of Dataset after Pre-processing.

Data Visualization - By this graph we get a clear idea about the average price of the dataset after preprocessing.

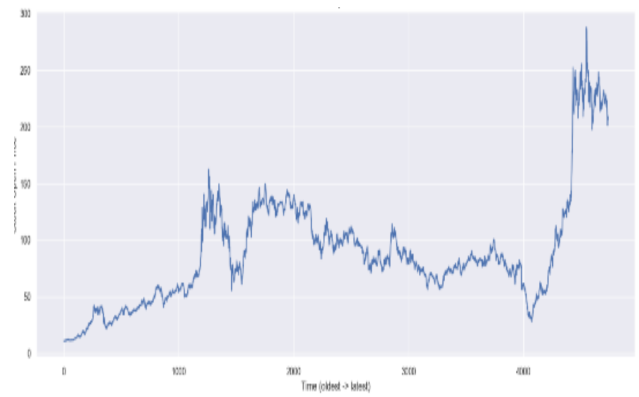

Fig. 7. Average Price Plot after Pre-processing.

By this graph, we get a clear idea about the return percentage of the dataset after pre-processing.

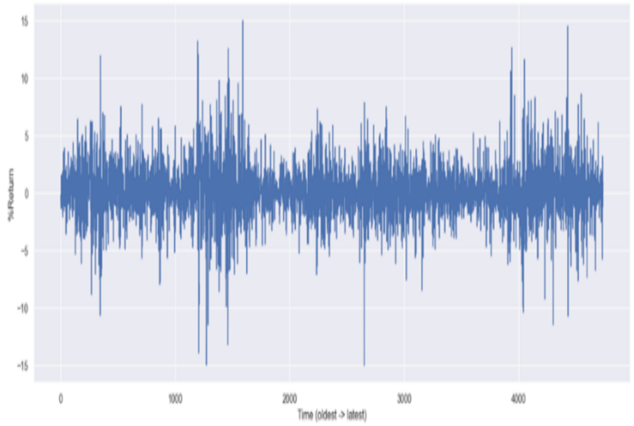

Fig. 8. TATA POWER Return Percentage Plot for the Given period.

The graph below represents the overall return percentage over the given period.

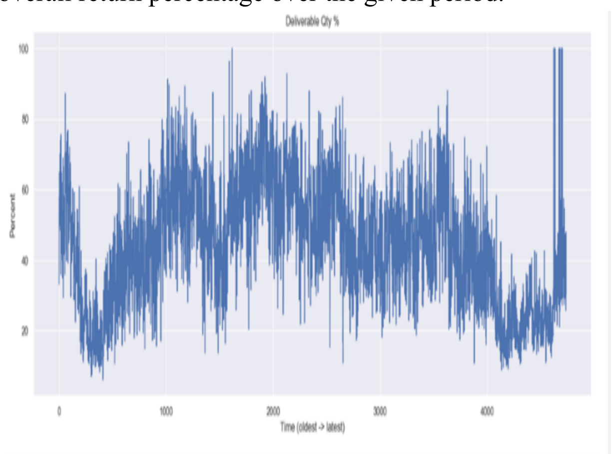

Fig. 9. Percent Plot of Deliverable Quantity to Traded Qty.

As we can observe, a symmetric curve, also known as the "Bell Curve", is symmetrical from the mean point to both halves of the curve. Hence, this graph evenly distributes the price data [11].

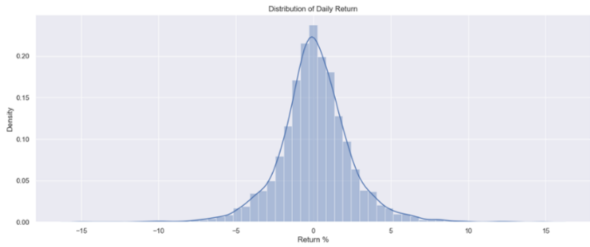

Fig. 10. Distribution Plot of Daily Return % based on Return % & Density.

The graph below represents the local maxima from the frequently appearing quantities in the data and the local minima from the frequently analysed quantities.

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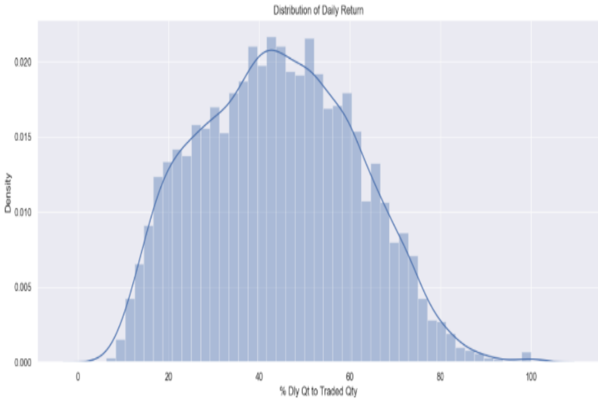


Fig. 11. Density Distribution % Deliverable Qty to Traded Qty...

The graph below is the representation study of the deliverable quantity effects on the stock price movement of the data.

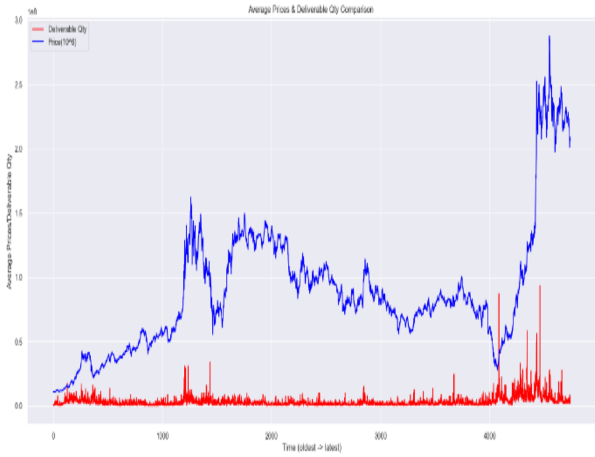


Fig. 12. Representing Prices on Graph (Average Prices & Deliverable Qty. Comparison) for TATA POWER.

Fig. 13. Representing Prices on Graph (Average Prices & Deliverable Qty. Comparison) for ITC.

4.7.7. The below scatterplot is the representation of the deliverable qty to the number of trades in a plot

Fig. 14. Potting a scatter plot of the Distribution of the Number of Trades to the Deliverable Qty. for TATA POWER.

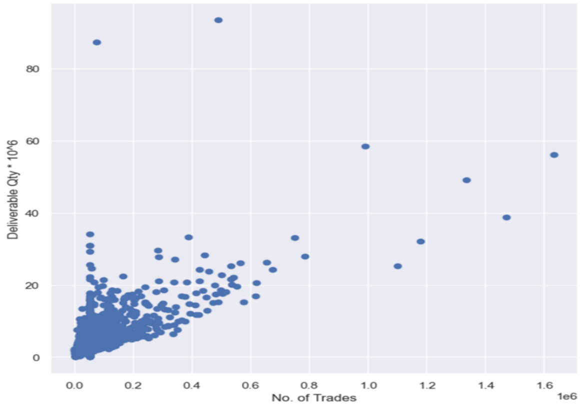
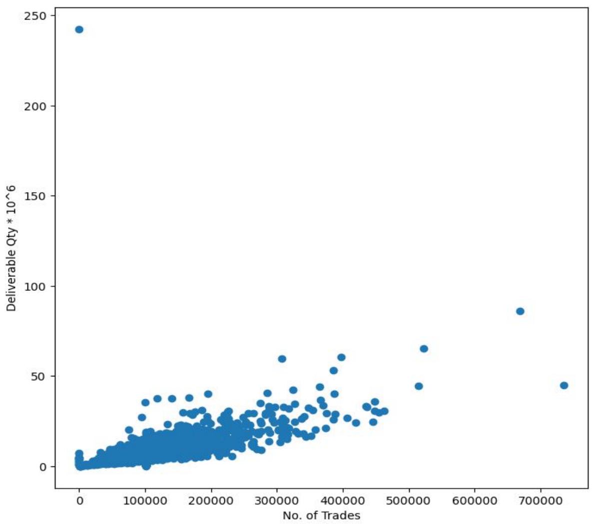


Fig. 15. Potting a scatter plot of the Distribution of the Number of Trades to the Deliverable Qty. for ITC.



The below graph is the representation of all the prices on the graph. It means that all the graphs are similar, and the prices are not varied. Therefore, the dataset contains no variations, and the data is processed for applying machine learning algorithms and predicting the results.

Distribution of Open, Close, High, and Low Price Comparison.

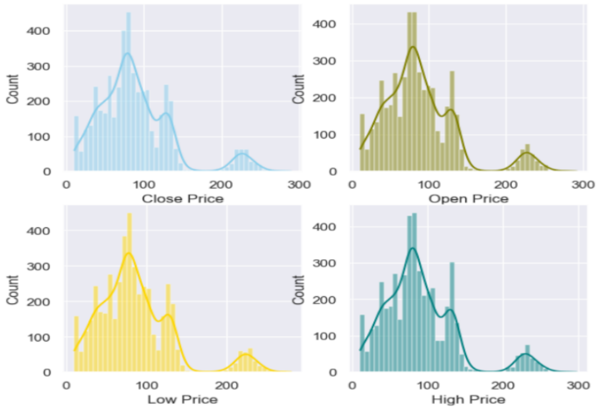


Fig. 16. Density Distribution % Deliverable Qty. to Traded Qty. for TATA POWER.

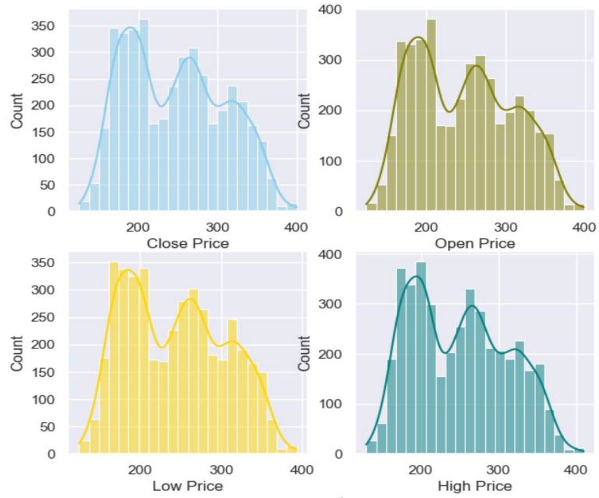


Fig. 17. Density Distribution % Deliverable Qty. to Traded Qty. for ITC.

CONCLUSION

This research shows analytical evidence on the TATA POWER and ITC datasets. Firstly, we created a structure to analyze the raw data. Secondly, we evaluated the dataset and performed Exploratory Data Analysis. The analysis results described a pattern through which we can gain a deeper understanding of the data. Our objective is to comprehend various models and studies that have been normalizing the price data of the stock, which causes the price to be fixed in each range, which is not valid in real-world scenarios; hence, such models will produce inaccurate predictions over a period. The proposed research concludes that our data set is now prepared for further training and testing and to apply Algorithms used in machine learning. The analysis results described a pattern through which we can gain a deeper understanding of the data. This paper discusses Daily Return % as an alternative to the close price.

As a result, data analysis looks at cleaning, converting, and modeling data to find insightful information and guide decisions. To comprehend and synthesize data and find patterns and trends, includes employing statistical and analytical approaches. Data analysis is crucial to data science, business analytics, and other disciplines that rely on data-driven decision-making. It can be applied to various data formats, including numerical, categorical, and textual data. Data analysis is a crucial phase in the data science process since it assists in transforming unstructured data into insights that can guide company decisions and strategies.

There is a vast body of research on data analysis, and it is an active area of study in statistics, computer science, and data science [28][31]. For example, advances in machine learning algorithms and the proliferation of big data have led to new approaches for analyzing and extracting insights from large and complex datasets.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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