Stock Market Prediction: Using Exponential Smoothing for Price Forecasting and SVM for Sales Volume Prediction

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***Abstract*—This Analysis and prediction of stock market trajectory have been a highly incentivized field of interest to researchers and investors alike. The purpose of this study is to forecast the stock prices and sales volume of a domestic and an international company and ultimately shedding light on the comparative predictability of both markets. Using various Exponential Smoothing models, we forecasted selling price for three consecutive days; furthermore, attempts were made using Support Vector Machines to predict stock sales volume. In doing so, we were able to predict the selling price with reasonable accuracy and demonstrated the apparent contrast between the domestic and international stock markets in terms of predictability.**

Keywords—Time Series, Stock Price Forecasting, Exponential Smoothing, Support Vector Machines, Dhaka Stock Exchange

I. Introduction

Predicting stock market trends has become a lucrative topic for contemporary research efforts in both the financial and computer-science sectors due to the monetary incentives associated with this field. Combining machine learning with the vast amount of readily available stock market data can lead to useful insights that may help investors make better informed decisions and help individuals and companies come up with better long and short-term investment strategies [1]. Two types of stock market prediction strategies are used by contemporary researchers and analysts, namely, technical analysis and fundamental analysis [2]. Technical analysis uses past trends in stock prices and sales volumes to predict future directions. Whereas fundamental analysis concerns itself with the companies themselves and focuses on unstructured data such as financial news or earning reports that indicates a company's past performance. Due to the nature of the corresponding data, when it comes to integrating machine learning with these prediction strategies, the fundamental approach uses text mining techniques [3] whereas the technical approach utilizes methods such as time series forecasting, regression analysis or support vector machines [4]. In this paper, we have used several Exponential Smoothing models to predict stock prices and Support Vector Machine (SVM) to predict daily sales volume of a given stock. In the stock market, daily sales volume of a company refers to the amount of its financial assets that has been traded within a single day, whereas closing price indicates the last price a particular stock was traded on a given day.

Time series forecasting refers to the process of predicting a value that will appear in a sequence of values in the future by taking past observations into account [5]. Exponential smoothing is a technique for forecasting time series data with features such as trend, seasonality and cyclicity [6]. Thus such an approach can be suitable for stock price prediction since stock prices recorded over regular time intervals can be represented as a time-series and the prices of stocks do follow upward and downward trends from time to time. The Oracle Machine Learning cloud platform was used to implement this project, which provided us with several different exponential smoothing and support vector machine models to apply to our data.

For our research, we targeted Grameenphone from Dhaka Stock Exchange and Apple as a representative of the international stock market. The stock market data of the companies was collected from public sources on Kaggle. Forecasting how stock markets will behave is extremely difficult due to the plethora of different factors that influence it. These factors could be economic as well as social, political, environmental, or simply stem from the investor's personal biases. Thus it is nigh impossible to build a model that will accurately take into account every single one of these factors and predict an accurate outcome. Such a daunting task is further complicated by the unusually volatile nature of Bangladeshi stock exchanges, which is evident from past events such as the 2011 Bangladesh stock market crash [7]. Despite said limitations, our prediction approaches have shown promising results, especially when it came to predicting the closing price for a stock for three consecutive days based on previous observations in the time series data. On the other hand, SVM was also able to predict the upward or downward trend of stock sales volume in most cases; however, it could not accurately predict the sales volume itself. Furthermore, after running the same simulations on both of the company's data, we found that Apple's stock prices were relatively more predictable than Grameenphone's stock prices.

II. Literature Review

Machine learning, deep learning, neural network techniques are becoming increasingly popular for forecasting stock prices. SVM, Neural Network, Linear Regression, KNN, and Naive Bayesian are some of the machine learning models used in the past for stock prediction. [1] utilizes Holt's exponential smoothing for predicting time series data. In this paper, Holt's exponential smoothing was combined with Multi-layered Perceptrons to create a hybrid methodology to forecast time series data. In [2], Faria et al. (2009) found out that the neural networks fared better in predicting time series data when compared to exponential smoothing. In [3], Khaidem et al. (2016) proposed an unprecedented way to formulate a better investment plan from the insights gained about the returns of a particular stock from ensemble learning. In [4], Support Vector Machine was utilized to predict stock market trends. The proposed SVM-based strategy was applied to Taiwanese stock market data which yielded better results when compared to traditional forecasting methods. Cao et al. (2012) in [5] conducted fundamental analysis through gathering information gained from the internet and financial markets and performing sentiment analysis which were later combined with the stock price and SVM to forecast stock market trends with greater accuracy.

III. Methodology

The goal of this research can be dissected into two portions. Firstly, we want to predict the future closing price of stocks based on prior observations. Furthermore, we want to determine the feasibility of predicting the stock sales volume based on past observations and closing prices. To do so, we are using Oracle's Machine Learning Cloud and it's built-in machine learning models.

Stock prices are recorded over regular time intervals, and thus can be considered as time series; hence, we propose using different variants of Exponential Smoothing algorithms to forecast the closing prices of three consecutive days of a domestic company (Grameenphone) and a foreign company (Apple). The essence of time series can be decomposed into four components; trends, seasonality, cyclicity, and noise. Firstly, trends refer to the tendency to increase or decrease in value. Secondly, seasonality is the recurring trends over a certain time interval. Thirdly, cyclicity refers to the trends that do not occur in fixed time frequencies. Lastly, noise is the outliers that do not have any rhyme and reasons. Taking these four components into accounts, there are different variants of Exponential Smoothing (ES); namely, Simple ES, Holt linear ES, Holt-Winters multiplicative ES, etc. For our model, we have chosen four models depending upon the aforementioned four time-series components.

- **Simple ES** (EXSM_SIMPLE): It uses the previous value and uses a smoothing constant to generate subsequent value.
- **ES with Multiplicative Damped Trend** (EXSM_MULTRD_DMP): It inherits the Simple ES model, however, improves it by taking into account trends. Furthermore, to reduce the effect of drastic fluctuations in values, it uses Multiplicative Dampening which dampens the trends exponentially.
- **Holt's ES with Linear Damped Trend** (EXSM_HOLT_DMP): Holt (1957) extended the Simple ES method to capture trends. In this particular model, trends are dampened additively.
- **Holt-Winters Additive ES with Damped Trend** (EXSM_DHW_ADDSEA): Winters (1960) extended the aforementioned Holt's ES model to include seasonality. In this model, seasonality is dampened additively.

Even though the stock market does not follow any seasonal patterns, we still want to verify whether it yields any constructive outcomes. Furthermore, we are using 95% confidence level and days as intervals between data points. Moreover, we took Apple and GP's stock market data from 2016 to 2019 and separated the last three data points that would later be predicted by the ES model, later on, we compared the predicted values and the actual values to evaluate the accuracy of our model.

Trading volumes are determined by the stock prices and the external factors surrounding a particular trading company. Even though it is predominantly determined by external factors, the stock price has a significant role in the sales volume. As a result, we want to determine the sales volume depending solely upon the stock price. To do so, we are using the Support Vector Machine's (SVM) regression model. We are using linear kernel function and Convergence tolerance of 0.0001. Furthermore, we have taken Apple and GP's stock market data from 2016 to 2019 and split it into train and test datasets with a 7:3 ratio. There have been numerous works based upon forecasting the stock price using SVM; however, according to our knowledge, sales volume prediction with SVM has not been conducted yet. As a result, we are uncertain about this model's performance.

IV. Results

A. Closing Price Prediction with Exponential Smoothing

Fig-1: Training Grameenphone's dataset with Exponential Smoothing

Fig-2: Training Apple's dataset with Exponential Smoothing

Tables I and II represent the errors in training the dataset with four different models.

TABLE I. Errors in fitting Grameenphone's dataset into different ES models

	EXSM_SIMPLE	EXSM_MULTRD_DMP	EXSM_HOLT_DMP	EXSM_DHW_ADDSEA
MAE	3.0488	0.0086	3.0488	3.1525
MSE	20.6887	20.7007	20.4886	21.1963
STD	4.5485	4.5498	4.5264	4.6039

TABLE II. Apple's forecasted values of different ES models

	EXSM_SIMPLE	EXSM_MULTRD_DMP	EXSM_HOLT_DMP	EXSM_DHW_ADDSEA
MAE	0.6136	0.0122	0.6069	0.6794
MSE	1.1477	1.1233	1.1256	1.2678
STD	1.0713	1.0598	1.0609	1.126

It is evident that Holt's ES with Linear Damped Trend performs well consistently.

TABLE III. Apple's forecasted values of different ES models

	Actual Value	EXSM_SIMPLE	EXSM_MULTRD_DMP	EXSM_HOLT_DMP	EXSM_DHW_ADDSEA
2020-AUG-26	126.5225	124.915	125.602	125.466	125.685
2020-AUG-27	125.01	124.915	126.141	125.886	126.200
2020-AUG-28	124.807	124.915	126.599	126.298	127.008

TABLE IV. Grameenphone's forecasted values of different ES models

	Actual Value	EXSM_SIMPLE	EXSM_MULTRD_DMP	EXSM_HOLT_DMP	EXSM_DHW_ADDSEA
2019-DEC-23	288.8	284.200	284.195	283.913	283.809
2019-DEC-24	287.2	284.200	284.190	283.683	283.633
2019-DEC-25	286.9	284.200	284.183	283.352	283.195

Table V and VI represent errors in forecasting the subsequent values.

TABLE V. Errors in forecasted values of Grameenphone

	EXSM_SIMPLE	EXSM_MULTRD_DMP	EXSM_HOLT_DMP	EXSM_DHW_ADDSEA
MAE	3.43	3.44	3.98	3.38
MSE	12.48	12.55	16.28	12.15
RMSE	3.43	3.54	4.03	3.49

TABLE VI. Errors in forecasted values of Apple

	EXSM_SIMPLE	EXSM_MULTRD_DMP	EXSM_HOLT_DMP	EXSM_DHW_ADDSEA
MAE	0.6	1.28	1.14	0.6794
MSE	0.87	1.78	1.37	1.2678
STD	0.93	1.33	1.17	1.126

Here, our models can predict the values of Apple more accurately than GP. In both cases, Simple ES performs well, however, this should not be the case as it does not take trends into account.

B. *Predicting Trends in Stock Sales Volume Using SVM*

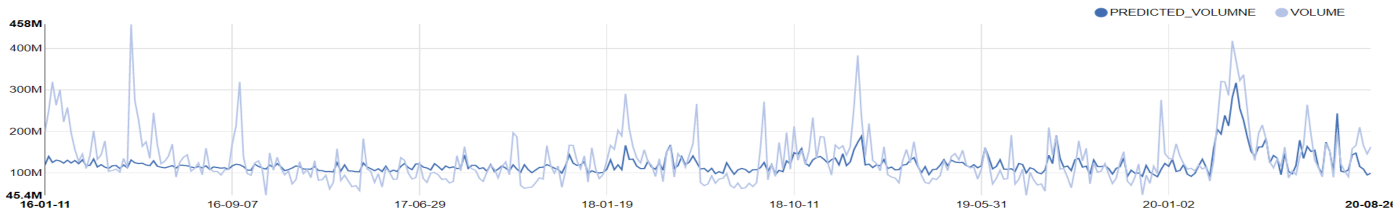

Fig-3: Actual volume vs predicted volume of Apple.

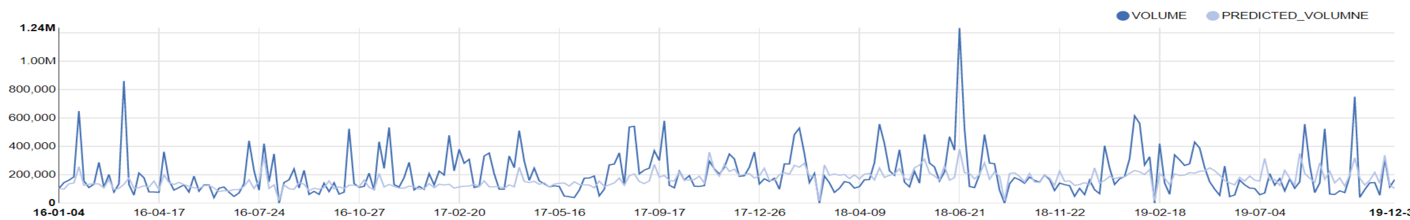

Fig-4: Actual volume vs predicted volume of Grameenphone.

Here, even though, our model was not able to accurately predict the exact volume of stock sales, it nonetheless predicted the trajectory of the trends reliably in some cases.

V. Discussion and Future Works

Our models were successful to forecast the price of the stocks quite accurately. However, there is a significant difference between the predictability of the domestic and foreign markets. Table III and VI shows that the foreign market could be predicted quite accurately with all of the models; in contrast, the prediction attempts of the domestic market yielded greater levels of error. This can be attributed to the relatively unpredictable nature of the domestic market. This goes to show that the domestic market is more reliant on the externals factors rather than the trajectory of the values.

Our SVM model did predict the trajectory of the sales volume trends to an extent, however, it fails to predict the exact volume of the sales itself. We propose attempting the same research with neural networks, we do believe it has the potential the yield a better outcome.

Lastly, we had a preconceived notion that stock market price and volume can not be predicted accurately. More often than not, the stock market is predominantly driven by externals factors. However, we did manage to predict the closing price to a certain extent, but, attempts to predict the sales volume based on price alone while disregarding external factors were proven unsuccessful.

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