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DIGITAL SIGNAL PROCESSING FOR PREDICTING STOCK PRICES

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ABSTRACT: *With the exponential growth of big data and data warehousing, the amount of data collected from various stock markets around the world has increased significantly. It is now impossible to process and analyze data using mathematical techniques and basic statistical calculations to forecast trends such as closing and opening prices, as well as daily stock market lows and highs. The development of smart and automated stock market forecasting systems has made significant progress in recent years. Digital signal processing is required for analysis and preprocessing because of the accuracy and speed with which these large amounts of data must be processed and analyzed. In this paper, we evaluate some of these predictive algorithms based on three parameters such as speed, accuracy and complexity, we analyze the data using the dataset from kaggle.com and we implement these algorithms using pythons. The results of our analysis in this paper shows a significant correlation between the yearly prices until the year 2018 where there is a significant increase in stock price.*

KEYWORDS: Digital Signal Processing, Forecasting, Prediction, Predictive algorithm, Stock Market

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INTRODUCTION

Stock index forecasting has always been a fascinating and pressing topic. Predicting stock market behaviour using various techniques and methods is a useful tool for investors to act with greater certainty, taking into account the risks and volatility of an investment, and knowing when to buy at the lowest price and sell at the highest price. Increases and decreases in stock market prices are influenced by a variety of factors such as demand, exchange rates, gold and oil prices, political and economic events, and so on. On the other hand, we can look at stock market price variation as a time series and ignore the aforementioned factors.

The upward and downward movement of stock market prices is influenced by several factors, including the amount of demand, the exchange rate, the price of oil, as well as political and economic trends. Price dispersion in the stock market can be viewed as a time series, and price predictions can be made in the future simply by determining the sequence rules of the price train. When new information is released in the financial market, predictive tools can be used on historical stock data to forecast the future.

Nonetheless, because most stock market data can be viewed as discrete signs (values examined at regular intervals such as hourly, daily, monthly, or yearly), it was relatively easy to adapt existing channel strategies for financial exchange analysis. In any case, the calculations must include the following two primary characteristics:

- Accuracy was critical because most stock market predictions must be made in real-time and must be accurate and precise; otherwise, major financial losses could result. To achieve this, the filters must be dynamic, able to adapt to a variety of factors and changes in real-time and make predictions accordingly. This necessitated the use of feedback in prediction algorithms, which led to the development of Adaptive Filters.
- Speed and ability to process large amounts of data: Stock market trends are influenced by a variety of factors such as stock price history, previous day closing prices, opening prices, daily highs and lows, as well as external factors such as market trends of different countries, and so on. All of this results in a large amount of data that must be processed in a short amount of time in order to make accurate predictions.

The paper concentrate on the application of adaptive filters to the study of stock market trends. Adaptive filters are recursive, and they use feedback to correct errors. This qualifies them to make accurate predictions because they can account for market volatility. For the stock market, data is typically available in the form of charts (histograms, pie charts, etc.) or as a time series.

Stock file prediction has always been a tempting and enticing field. Anticipating financial exchange behaviour through strategies and various techniques is a valuable tool to assist speculators in acting with more prominent certainty, confronting the challenges and unpredictability of a venture into thought, and understanding when to purchase the least expensive cost and when to offer to the most exorbitant cost. Increases and decreases in financial exchange costs are influenced by a variety of factors, such as interest rate, conversion scale, gold price, oil price, political and monetary events; however, from another perspective, we can consider the securities exchange cost variation as a time arrangement and without reference to the aforementioned variables, and only by determining the succession rules of cost. The goal here is to achieve a reasonable level of accuracy by employing two different prediction models and then comparing the results using the mean squared error. The variable

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being predicted is today's closing price and opening price using either the previous day's opening, low, high and adjusted close price or using a time series of the closing prices. The first step is to collect and analyze large amounts of historical data. Data scraping is a concept that has been used. The Gradient descent/Steepest descent algorithm is the first. This linear regression algorithm seeks to generate a hypothesis function that is as close to the correct output signal as possible. Linear regression is, at its core, curve fitting. A curve is plotted using the set of input training data, the equation of which is the hypothesis function. The cost of work is the mean squared difference between the expected and actual yield. The limited cost function aids in weight updating and hypothesis function improvement. The following algorithm is a simplified version of Prony's Normal Equation algorithm, which can register the arrangement in a single step, whereas inclination drop would require multiple steps. All shaft frameworks have a little more computational flexibility than the broader post zero models. The shafts are used to make the Normal Equation larger. The posts are discovered in order to reduce the squared error. The model is especially useful for forecasting transient prices. Financial analysts who invest in the stock market are frequently unaware of market trends. They're having trouble trading because they don't fully understand which stocks to buy or sell to make a profit. In today's world, all stock market information is readily available. Analyzing all of this data individually or manually is extremely difficult. This is where data mining techniques come in handy. Understanding that numerical time series analysis yields close results, intelligent investors use machine learning techniques to forecast stock market behaviour. This will enable financial analysts to predict the behaviour of the stock in question and act accordingly.

Because the price is everything in the stock market and is influenced by many factors such as season, change of government, policymakers' decisions, and so on, there is a need for a system capable of predicting future prices with some degree of accuracy. This paper tends to address the problem of using traditional statistics and mathematical techniques in analysing data and predicting trends like the stock market. This paper aims to develop a digital signal processing for predicting stock prices using python. We use data from kaggle.com to create input to our system and we apply python programming language for implementation.

LITERATURE REVIEW

Digital Signal Processing

Digital signal processing is the mathematical manipulation of an information signal, such as audio, temperature, voice, or video, to modify or improve it in some way. DSP filters, measures, compresses and produces analogue signals by manipulating various types of signals. Digital signals take information and convert it into binary format, where each bit of data is represented by two distinct amplitudes. Analogue signals take information and convert it into varying amplitude electric pulses, whereas digital signals take information and convert it into binary format, where each bit of data is represented by two distinct amplitudes. Analogue signals can be represented as sine waves, whereas digital signals can be represented as square waves. DSP is used in almost every field, including oil processing, sound reproduction, radar and sonar, medical image processing, and telecommunications—basically, any application that compresses and reproduces signals (Donald, 2015)

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Stock Market Prediction

The act of attempting to predict the future value of company stock or other financial instrument traded on an exchange is known as the stock market prediction. A successful forecast of a stock's future price could result in a large profit. Stock prices, according to the efficient-market hypothesis, reflect all currently available information, and any price changes that are not based on newly revealed information are thus inherently unpredictable. Others disagree, and those who hold this viewpoint claim to have a variety of methods and technologies that allow them to obtain future price information (Wikipedia, 2009). According to the efficient market hypothesis, stock prices are a function of information and rational expectations, and newly revealed information about a company's prospects is reflected almost immediately in the current stock price. This would imply that all publicly available information about a company, including its price history, is already reflected in the stock's current price. As a result, stock price changes reflect the release of new information, changes in the market as a whole, or random movements around a value that reflects the existing information set. In his influential 1973 book A Random Walk Down Wall Street, Burton Malkiel claimed that stock prices could not be predicted accurately by looking at price history. As a result, according to Malkiel, stock prices are best described by a statistical process known as a "random walk," which implies that daily deviations from the central value are random and unpredictable. As a result, Malkiel came to the conclusion that paying financial services professionals to forecast the market harmed, rather than helped, net portfolio return. Several empirical tests back up the theory's general applicability, as most professional stock predictors' portfolios do not outperform the market average return.

Sharma and Kaushik's (2018) research centred on attempting to answer the question of whether or not real stock prices can be forecasted – the forecastability of real stock prices. The research employed what he referred to as the martingale hypothesis, which primarily considered the predictability of price changes or returns. Finally, the study took into account efficient market theory. As a result, stock market prices are a reliable variable that can be influenced by a simple social media tweet.

Granger (1992) looked at a variety of methods and algorithms for forecasting stock market prices. While each algorithm and approach has its own set of advantages, it was discovered that the Long Short Term Memory (LSTM) and Neural Network methods outperformed the others.

Singh (2018) developed a predicting system by combining machine learning and deep learning techniques with Python code. Different algorithms, such as k-Nearest Neighbours, Linear Regression, and moving average, were used in the research.

RESEARCH METHODOLOGY

Recent stock market data were collected from www.kaggle.com. The data contain the date of the market activity, opening and closing stock, highest and lowest stock and volume. We analyzed the data using digital signal processing with the help of the python programming language for implementation. By plotting the stocks in form of signals, we were able to predict stock price. Table 1 shows the data set.

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Table 1: Data Set from www.kaggle.com

Date	Open	High	Low	Close	Close	Volume
1/2/2018	1048.34	1066.94	1045.23	1065	1065	1237600
1/3/2018	1064.31	1086.29	1063.21	1082.48	1082.48	1430200
1/4/2018	1088	1093.57	1084.002	1086.4	1086.4	1004600
1/5/2018	1094	1104.25	1092	1102.23	1102.23	1279100
1/8/2018	1102.23	1111.27	1101.62	1106.94	1106.94	1047600
1/9/2018	1109.4	1110.57	1101.231	1106.26	1106.26	902500
1/10/2018	1097.1	1104.6	1096.11	1102.61	1102.61	1042800
1/11/2018	1106.3	1106.525	1099.59	1105.52	1105.52	978300
1/12/2018	1102.41	1124.29	1101.15	1122.26	1122.26	1720500
1/16/2018	1132.51	1139.91	1117.832	1121.76	1121.76	1575300
1/17/2018	1126.22	1132.6	1117.01	1131.98	1131.98	1198700
1/18/2018	1131.41	1132.51	1117.5	1129.79	1129.79	1198200
1/19/2018	1131.83	1137.86	1128.3	1137.51	1137.51	1778200
1/22/2018	1137.49	1159.88	1135.11	1155.81	1155.81	1618000
1/23/2018	1159.85	1171.627	1158.75	1169.97	1169.97	1333100
1/24/2018	1177.33	1179.86	1161.05	1164.24	1164.24	1416600
1/25/2018	1172.53	1175.94	1162.76	1170.37	1170.37	1480500
1/26/2018	1175.08	1175.84	1158.11	1175.84	1175.84	2018800
1/29/2018	1176.48	1186.89	1171.98	1175.58	1175.58	1378900
1/30/2018	1167.83	1176.52	1163.52	1163.69	1163.69	1556300
1/31/2018	1170.57	1173	1159.13	1169.94	1169.94	1538700
2/1/2018	1162.61	1174	1157.52	1167.7	1167.7	2412100
2/2/2018	1122	1123.07	1107.278	1111.9	1111.9	4857900
2/5/2018	1090.6	1110	1052.03	1055.8	1055.8	3798300
2/6/2018	1027.18	1081.71	1023.137	1080.6	1080.6	3448000
2/7/2018	1081.54	1081.78	1048.26	1048.58	1048.58	2369200
2/8/2018	1055.41	1058.62	1000.66	1001.52	1001.52	2859100
2/9/2018	1017.25	1043.97	992.56	1037.78	1037.78	3505900
2/12/2018	1048	1061.5	1040.928	1051.94	1051.94	2057700
2/13/2018	1045	1058.37	1044.087	1052.1	1052.1	1265100
2/14/2018	1048.95	1071.72	1046.75	1069.7	1069.7	1555800
2/15/2018	1079.07	1091.479	1064.34	1089.52	1089.52	1843400
2/16/2018	1088.41	1104.67	1088.313	1094.8	1094.8	1681600
2/20/2018	1090.57	1113.95	1088.52	1102.46	1102.46	1423100
2/21/2018	1106.47	1133.97	1106.33	1111.34	1111.34	1512900
2/22/2018	1116.19	1122.82	1102.59	1106.63	1106.63	1317200
2/23/2018	1112.64	1127.28	1104.714	1126.79	1126.79	1261000
2/26/2018	1127.8	1143.96	1126.695	1143.75	1143.75	1559100
2/27/2018	1141.24	1144.04	1118	1118.29	1118.29	1774100
2/28/2018	1123.03	1127.53	1103.24	1104.73	1104.73	1882600

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3/1/2018	1107.87	1110.12	1067.001	1069.52	1069.52	2515900
3/2/2018	1053.08	1081.999	1048.115	1078.92	1078.92	2271600
3/5/2018	1075.14	1097.1	1069	1090.93	1090.93	1202200
3/6/2018	1099.22	1101.85	1089.775	1095.06	1095.06	1532800
3/7/2018	1089.19	1112.22	1085.482	1109.64	1109.64	1292500
3/8/2018	1115.32	1127.6	1112.8	1126	1126	1355100
3/9/2018	1136	1160.8	1132.461	1160.04	1160.04	2128000
3/12/2018	1163.85	1177.05	1157.42	1164.5	1164.5	2172300
3/13/2018	1170	1176.76	1133.33	1138.17	1138.17	1907200
3/14/2018	1145.21	1158.59	1141.44	1149.49	1149.49	1291400
3/15/2018	1149.96	1161.08	1134.54	1149.58	1149.58	1395400
3/16/2018	1154.14	1155.88	1131.96	1135.73	1135.73	3092000
3/19/2018	1120.01	1121.99	1089.01	1099.82	1099.82	2805900
3/20/2018	1099	1105.2	1083.46	1097.71	1097.71	1831900
3/21/2018	1092.74	1106.3	1085.15	1090.88	1090.88	1878900
3/22/2018	1081.88	1082.9	1045.91	1049.08	1049.08	2667000
3/23/2018	1047.03	1063.36	1021.22	1021.57	1021.57	2156700
3/26/2018	1046	1055.63	1008.4	1053.21	1053.21	2665100
3/27/2018	1063	1064.839	996.92	1005.1	1005.1	3095300
3/28/2018	998	1024.23	980.64	1004.56	1004.56	3369300
3/29/2018	1011.63	1043	1002.9	1031.79	1031.79	2726800
4/2/2018	1022.82	1034.8	990.37	1006.47	1006.47	2680400
4/3/2018	1013.91	1020.99	994.07	1013.41	1013.41	2275100
4/4/2018	993.41	1028.718	993	1025.14	1025.14	2484700
4/5/2018	1041.33	1042.79	1020.131	1027.81	1027.81	1363000
4/6/2018	1020	1031.42	1003.03	1007.04	1007.04	1746400
4/9/2018	1016.8	1039.6	1014.08	1015.45	1015.45	1751600
4/10/2018	1026.44	1036.28	1011.34	1031.64	1031.64	1974500
4/11/2018	1027.99	1031.364	1015.87	1019.97	1019.97	1483900
4/12/2018	1025.04	1040.69	1021.435	1032.51	1032.51	1357000
4/13/2018	1040.88	1046.42	1022.98	1029.27	1029.27	1223000
4/16/2018	1037	1043.24	1026.74	1037.98	1037.98	1211200
4/17/2018	1051.37	1077.88	1048.26	1074.16	1074.16	2320300
4/18/2018	1077.43	1077.43	1066.225	1072.08	1072.08	1344100
4/19/2018	1069.4	1094.165	1068.18	1087.7	1087.7	1747700
4/20/2018	1082	1092.35	1069.57	1072.96	1072.96	1889700
4/23/2018	1077.86	1082.72	1060.7	1067.45	1067.45	2341300
4/24/2018	1052	1057	1010.59	1019.98	1019.98	4760300
4/25/2018	1025.52	1032.49	1015.31	1021.18	1021.18	2391100
4/26/2018	1029.51	1047.98	1018.19	1040.04	1040.04	2079500
4/27/2018	1046	1049.5	1025.59	1030.05	1030.05	1619800
4/30/2018	1030.01	1037	1016.85	1017.33	1017.33	1671300

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5/1/2018	1013.66	1038.47	1008.21	1037.31	1037.31	1427900
5/2/2018	1028.1	1040.389	1022.87	1024.38	1024.38	1603100
5/3/2018	1019	1029.675	1006.29	1023.72	1023.72	1815100
5/4/2018	1016.9	1048.51	1016.9	1048.21	1048.21	1938700
5/7/2018	1049.23	1061.68	1047.1	1054.79	1054.79	1466100
5/8/2018	1058.54	1060.55	1047.145	1053.91	1053.91	1217700
5/9/2018	1058.1	1085.44	1056.365	1082.76	1082.76	2032800
5/10/2018	1086.03	1100.44	1085.64	1097.57	1097.57	1443000
5/11/2018	1093.6	1101.33	1090.91	1098.26	1098.26	1253700
5/14/2018	1100	1110.75	1099.11	1100.2	1100.2	1518100
5/15/2018	1090	1090.05	1073.47	1079.23	1079.23	1494900
5/16/2018	1077.31	1089.27	1076.26	1081.77	1081.77	1097300
5/17/2018	1079.89	1086.87	1073.5	1078.59	1078.59	1043800
5/18/2018	1061.86	1069.94	1060.68	1066.36	1066.36	1565200
5/21/2018	1074.06	1088	1073.65	1079.58	1079.58	1023200
5/22/2018	1083.56	1086.59	1066.69	1069.73	1069.73	1090000
5/23/2018	1065.13	1080.78	1061.71	1079.69	1079.69	1030000
5/24/2018	1079	1080.47	1066.15	1079.24	1079.24	756800
5/25/2018	1079.02	1082.56	1073.775	1075.66	1075.66	899400
5/29/2018	1064.89	1073.37	1055.22	1060.32	1060.32	1856900
5/30/2018	1063.03	1069.21	1056.83	1067.8	1067.8	1138500
5/31/2018	1067.56	1097.19	1067.56	1084.99	1084.99	3088300
6/1/2018	1099.35	1120	1098.5	1119.5	1119.5	2412000
6/4/2018	1122.33	1141.89	1122.005	1139.29	1139.29	1880000
6/5/2018	1140.99	1145.738	1133.19	1139.66	1139.66	1678000
6/6/2018	1142.17	1143	1125.743	1136.88	1136.88	1698200
6/7/2018	1131.32	1135.82	1116.52	1123.86	1123.86	1520000
6/8/2018	1118.18	1126.67	1112.15	1120.87	1120.87	1290800
6/11/2018	1118.6	1137.26	1118.6	1129.99	1129.99	1079300
6/12/2018	1131.07	1139.79	1130.735	1139.32	1139.32	912000
6/13/2018	1141.12	1146.5	1133.38	1134.79	1134.79	1506400
6/14/2018	1143.85	1155.47	1140.64	1152.12	1152.12	1343400
6/15/2018	1148.86	1153.42	1143.485	1152.26	1152.26	2122500
6/18/2018	1143.65	1174.31	1143.59	1173.46	1173.46	1413700
6/19/2018	1158.5	1171.27	1154.01	1168.06	1168.06	1621000
6/20/2018	1175.31	1186.286	1169.16	1169.84	1169.84	1648500
6/21/2018	1174.85	1177.295	1152.232	1157.66	1157.66	1238100
6/22/2018	1159.14	1162.497	1147.26	1155.48	1155.48	1311000
6/25/2018	1143.6	1143.91	1112.78	1124.81	1124.81	2157300
6/26/2018	1128	1133.21	1116.659	1118.46	1118.46	1563200
6/27/2018	1121.34	1131.836	1103.62	1103.98	1103.98	1293900
6/28/2018	1102.09	1122.31	1096.01	1114.22	1114.22	1072400
6/29/2018	1120	1128.227	1115	1115.65	1115.65	1315100

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DISCUSSION AND RESULT

Python is used to implement this system. From Fig 1, we noticed a very significance increase in the stock price in the year 2018 and their decrease afterwards down to asignificante system is capable of predicting stock price.

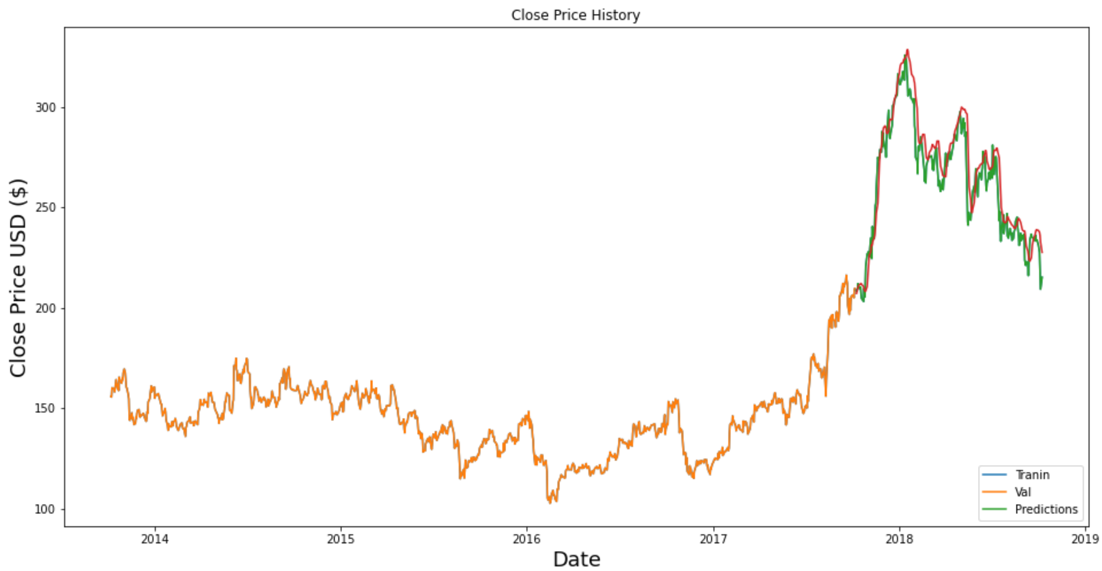

FIG 1: Stock Market Prediction

Date	Close	Predictions
2017-10-09	208.3	207.136383
2017-10-10	208.45	208.315948
2017-10-11	209.4	209.207306
2017-10-12	212.0	209.972534
2017-10-13	210.25	210.973175
...	...	...
2018-10-01	230.9	238.434036
2018-10-03	227.6	237.555710
2018-10-04	218.2	235.966064
2018-10-05	209.2	232.669464
2018-10-08	215.15	227.5667

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CONCLUSION

Predicting stock prices with some degree of accuracy is critical, especially because it assists business owners or investors in making sound decisions. Although accurate forecasting requires a high level of programming language and machine learning. Our analysis in this paper shows a significant correlation between the yearly prices until the year 2018 where there is a significant increase in stock price. Despite the fact that there are several challenges in our program and that our data collection can be improved, more research can be done, particularly to have refined search data and a better algorithm.

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