

Evaluation of Forecasting Methods from Selected Stock Market Returns

¹ Obulesu Varikunta, ² Madhupathi Yeswanth

¹ Assistant Professor, Department of Master of Business Administration, CMR Institute of Technology, Medchal, India.

² Department of Master of Business Administration, CMR Institute of Technology, Medchal, India.

Corresponding author.

Correspondence: Madhupathi Yeswanth
E-mail: yashwanthswamy3@gmail.com

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Abstract

Forecasting stock market returns is one of the most effective tools for risk management and portfolio diversification. There are several forecasting techniques in the literature for obtaining accurate forecasts for investment decision making. Numerous empirical studies have employed such methods to investigate the returns of different individual stock indices. However, there have been very few studies of groups of stock markets or indices. The findings of previous studies indicate that there is no single method that can be applied uniformly to all markets. In this context, this study aimed to examine the predictive performance of linear, nonlinear, artificial intelligence, frequency domain, and hybrid models to find an appropriate model to forecast the stock returns of developed, emerging, and frontier markets. We considered the daily stock market returns of selected indices from developed, emerging, and frontier markets for the period 2000–2018 to evaluate the predictive performance of the above models. The results showed that no single model out of the five models could be applied uniformly to all markets. However, traditional linear and nonlinear models outperformed artificial intelligence and frequency domain models in providing accurate forecasts.

INTRODUCTION

The evaluation of forecasting methods in the context of stock market returns is an essential aspect of financial analysis and investment strategy. This process involves assessing various predictive models to determine their accuracy and reliability in forecasting future stock prices or market trends. Different methods, ranging from traditional statistical models like ARIMA (Autoregressive Integrated Moving Average) and moving averages to more complex machine learning algorithms such as neural networks and decision trees, are utilized to predict market behavior. And the specific characteristics of the stocks or indices being analyzed. For instance, high-frequency trading requires extremely accurate short-term forecasts, while long-term investors might prioritize models that capture broader market trends over time.

This paper aims to compare and contrast the performance of different forecasting methods on selected stock market returns, providing insights into which models perform best under various

conditions and why. This analysis is vital for investors and analysts seeking to optimize their strategies in the ever-evolving landscape of the financial markets.

REVIEW OF LITERATURE

Cheng Zhao (2023) Predicting stock prices is crucial for stock market investing. However, the intricacy of stock price variables has been extensively examined. Traditional techniques that use time-series data for one stock lack a comprehensive view. TSRM uses stock transaction data to automatically classify stocks and determine stock link ages using a K-means algorithm. LSTM time series and graph convolution network (GCN) connection information are used to forecast stock prices. Compared to the baseline, the TSRM improved cumulative returns by 44% and 41% and reduced maximum drawdown by 4.9% and 6.6% in the Chinese Shanghai and Shenzhen stock markets.

Michael Biehl (2023) Accurate stock price forecasts require identifying essential factors that impact machine learning (ML) models. Stock market forecasting using ML, statistical, and deep learning approaches has been reviewed in many studies. No stock market forecasting survey has examined feature selection and extraction methods. This survey analyzes 32 feature study-ML research studies in stock market applications. We discuss some effective feature selection and extraction methods used in the articles' stock market assessments. We report and assess the performance of feature analysis and ML approaches. Other survey papers, stock market input and output data, and factor analysis are also available. For stock market applications,

Mostafa Shabani (2023) Cross-correlation analysis is a powerful tool for understanding the mutual dynamics of time series. This study introduces a new method for predicting the future state of synchronization of the dynamics of two financial time series. To this end, we use the cross recurrence plot analysis as a nonlinear method for quantifying the multidimensional coupling in the time domain of two-time series and for determining their state of synchronization.

Sudeepa Das (2022) Stock index price forecasting helps investors and financial investigators make decisions with maximum gain and minimal risk. To succeed, a powerful engine that can manage relevant data is needed. In this article, a modified crow search algorithm (CSA) and extreme learning machine enhance stock market predictions. Particle Swarm Optimization (PSO)-based Group orientated CSA (PGCSA) solves 12 benchmark issues better than other techniques. PGCSA method improves standard ELM by achieving suitable weights and biases. Performance measurements, technical indicators, and hypothesis testing (paired t-test) show how hybrid PGCSA ELM model predicts next-day closing prices of seven stock indexes. COVID-19 data is used to evaluate the seven stock indexes. Comparing this model to established approaches tests it. Simulation findings suggest PGCSAELM model can forecast following day closing price.

Daiyou Xiao (2022) Machine learning is a systematic and comprehensive use of computer algorithms and statistical models that is applied in many disciplines. Machine learning is mostly used to predict capital market prices in finance. This article used classical and machine learning methods to predict stock time-series data for linear and non-linear problems, respectively. First, New York Stock Exchange stock samples from 2010–2019 are gathered. Next, stock price and sub correlation are trained and predicted using the ARIMA and LSTM neural network models. Finally, we test the proposed model using several indicators and find that: (1) the ARIMA model and LSTM model accurately predict stock price and correlation; (2) the LSTM model outperforms ARIMA; and (3) the ensemble model of ARIMA-LSTM significantly outperforms other benchmark methods. For investors interested in China stock trading, our recommended approach offers theoretical assistance and method reference.

In this paper, we introduce a Deep Convolutional Generative Adversarial Network (DCGAN)

architecture to deal with the problem of forecasting the closing price of stocks. To test the empirical performance of our proposed model we use the FTSE MIB (Financial Times Stock Exchange Milano Indice di Borsa), the benchmark stock market index for the Italian national stockexchange. By conducting both single-step and multi-step forecasting, we observe that our proposed model performs better than standard widely used tools, suggesting that Deep Learning (and in particular GANs) is a promising field for financial time series forecasting.

Yee-Fan Tan (2021) Audience attention is vital in Digital Signage Advertising (DSA), as it has a significant impact on the pricing decision to advertise on those media. Various environmental factors affect the audience attention level toward advertising signage. as the environmental factors that could affect the audience attention are changing fast and are generally not considered in the current pricing solutions in a timely manner. Therefore, .However, it is difficult to determine an optimal price forecasting model for DSA with the increasing number of available time-series forecasting models in recent years. Based on the 84 research articles reviewed, the data characteristics analysis in terms of linearity, stationary, volatility, and dataset size is helpful in determining the optimal model for time-series price forecasting. This paper has reviewed the widely used time-series forecasting models and identified the related data characteristics of each model. A framework is proposed to demonstrate the model selection process for dynamic pricing in DSA based on its data characteristics analysis, paving the way for future research of pricing solutions for DSA.

RESEARCH METHODOLOGY

Sample size: - 3(Reliance, TC Sand ITC) Companies are taken Security products selected for NSE/BSE. (IT is Most Liquidity Industry in stock market)

RESEARCH GAP

Despite advancements in forecasting stock market returns, significant gaps remain. Brock et al. (1992) and Timmermann (2008) highlighted the need for comparative analyses across diverse markets. Zhang et al. (2019) introduced machine learning in forecasting, but more research is needed on the effectiveness of hybrid models. Pesaran and Timmermann (2004) focused on stable periods, leaving a gap in understanding methods during market turbulence. Clements and Hendry (2005) emphasized short-term forecasts, with long-term accuracy less explored. Bao and Yang (2020) used alternative data, but systematic evaluations in varied market conditions are lacking. Addressing these gaps could enhance forecasting reliability and effectiveness.

OBJECTIVES OF THE STUDY

- The main goal of a security forecast project is to learn more about security forecasting.
- The research may assist in the analysis of securities growth.
- To analyze the performance and measure of securities volatility using MACD analysis.

RESEARCH DESIGN

The study design will use a quantitative methodology to assess forecasting techniques using particular stock market results. It would include gathering historical data from many market places over a considerable amount of time on prices, volumes, and economic variables related to the stock market. This data will be subjected to a variety of forecasting models, which will include hybrid approaches, machine learning techniques, and conventional statistical methods. Metrics in clouding accuracy, mean absolute error(MAE), and root means square error (RMSE) will be used to

evaluate these models' performance. The advantages and disadvantages of each approach will be compared in order to shed light on how well-suited and dependable they are for various market conditions.

DATA ANALYSIS

ADF FOODS-2018-2019

Date	Close	3ema	5ema	Macd
September-18	216.70			
October-18	202.80	67.60		
November-18	269.55	89.85		
December-18	269.65	89.88	244.96	155.08
January-19	242.30	80.77	240.20	159.43
February-19	232.30	77.43	243.32	165.89
March-19	239.65	79.88	250.69	170.81
April-19	246.35	82.12	246.05	163.93
May-19	293.10	97.70	250.74	153.04
June-19	272.75	90.92	256.83	165.91
July-19	250.70	83.57	260.51	176.94
August-19	256.25	85.42	263.83	178.41



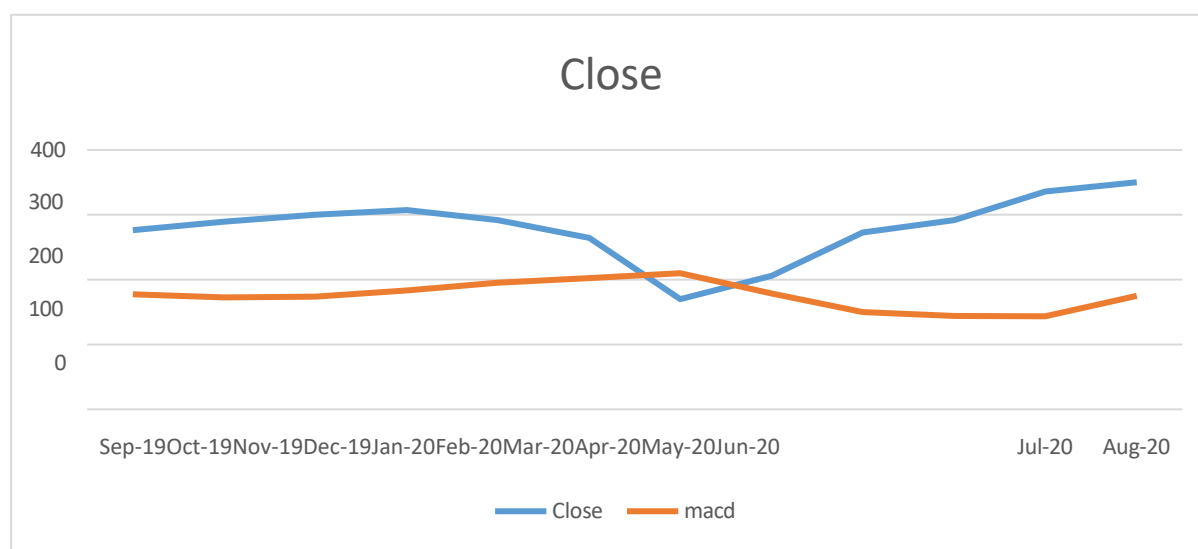
INTERPRETATION:-

- The stock price started at 216.70 in September 2018 and reached a high of 293.10 in May 2019.
- The 3ema and 5ema were both moving upwards, which indicates that the trend was bullish.
- The Macd was also moving up wards, which confirms the bullish trend.

Overall, the stock price data for ADF FOODS is bullish. The stock price has been trending up wards and the technical indicators are all pointing to further gains.

ADF FOODS-2019-2020

Date	Close	3ema	5ema	Macd
September-19	275.95	91.98	269.75	177.77
October-19	289.20	96.40	268.97	172.57
November-19	300.35	100.12	274.49	174.37
December-19	306.85	102.28	285.72	183.44
January-20	291.55	97.18	292.78	195.60
February-20	264.40	88.13	290.47	202.34
March-20	170.00	56.67	266.63	209.96
April-20	206.20	68.73	247.80	179.07
May-20	273.15	91.05	241.06	150.01
June-20	292.45	97.48	241.24	143.76
July-20	336.25	112.08	255.61	143.53
August-20	350.30	116.77	291.67	174.90

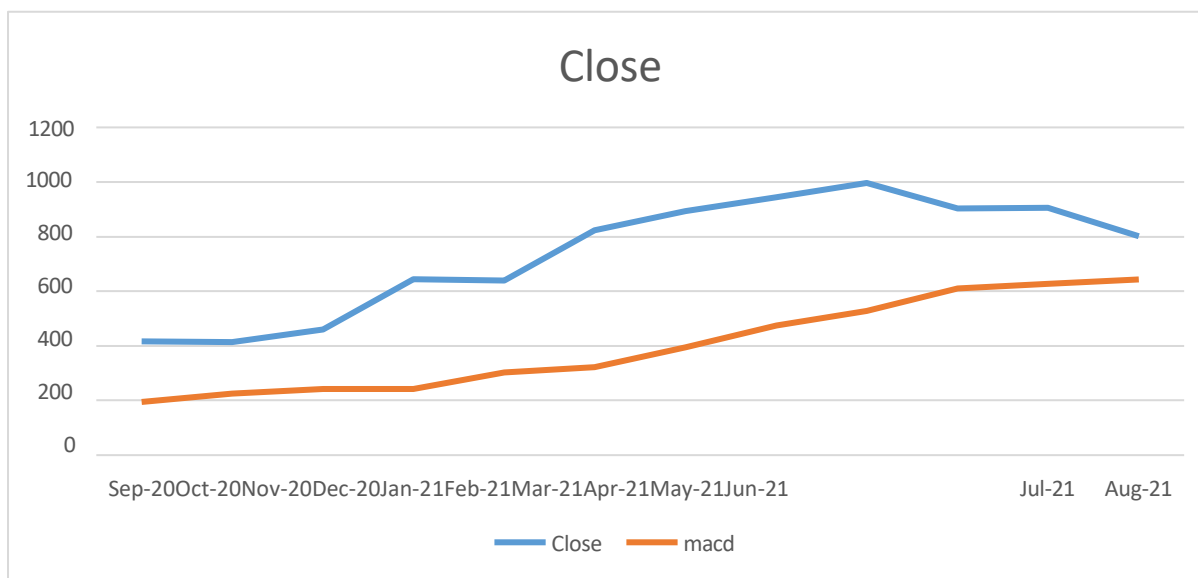
**INTERPRETATION:-**

- The stock price started at 275.95 in September 2019 and reached a high of 350.30 in August 2020.
- The 3ema and 5ema were both moving upwards, which indicates that the trend was bullish.
- The stock price experienced a sharp decline in March 2020, which was likely due to the COVID-19 pandemic.
- The stock price has since recovered and is currently trading above the 3ema and 5ema.

ADF FOODS-2020-2021

Date	Close	3ema	5ema	Macd
September-20	417.65	139.22	333.96	194.74
October-20	414.00	138.00	362.13	224.13
November-20	459.80	153.27	395.60	242.33
December-20	643.40	214.47	457.03	242.56
January-21	638.25	212.75	514.62	301.87

February-21	823.90	274.63	595.87	321.24
March-21	893.55	297.85	691.78	393.93
April-21	944.45	314.8167	788.71	473.8933
May-21	996.65	332.2167	859.36	527.1433
June-21	904.2	301.4	912.55	611.15
July-21	905.4	301.8	928.85	627.05
August-21	801.9	267.3	910.52	643.22

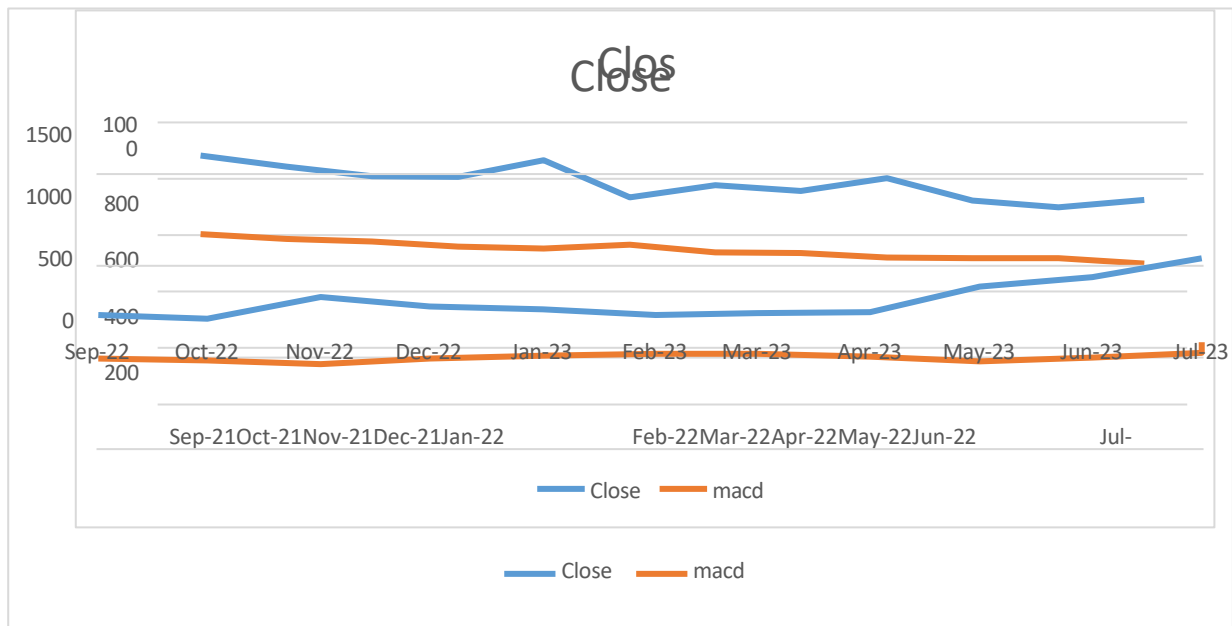


INTERPRETATION:-

- The stock price started at 417.65 in September 2020 and reached a high of 996.65 in May 2021.
 - The 3ema and 5ema were both moving up wards, which indicates that the trend was bullish.
- Overall, the stock price data for ADF FOODS is bullish. The stock price has been trending up wards and the technical indicators are all pointing to further gains.

ADF FOODS-2021-2022

Date	Close	3ema	5ema	Macd
September-21	882.65	294.22	898.16	603.94
October-21	844.00	281.33	867.63	586.30
November-21	810.00	270.00	848.79	578.79
December-21	807.25	269.08	829.16	560.08
January-22	865.20	288.40	841.82	553.42
February-22	734.95	244.98	812.28	567.30
March-22	778.25	259.42	799.13	539.71
April-22	757.95	252.65	788.72	536.07
May-22	802.45	267.48	787.76	520.28
June-22	722.35	240.78	759.19	518.41
July-22	699.05	233.02	752.01	518.99
August-22	725.55	241.85	741.47	499.62



INTERPRETATION:-

- The stock price started at 822.65 in September 2021 and reached a high of 865.20 in January 2022.
- The 3ema and 5ema were both moving upwards in the beginning of 2022, which indicate that the trend was bullish.
- However, the Mac started to decline in January 2022, which indicates that the trend was starting to become bearish.
- The stock price has been declining since January 2022, and is currently trading below the 3 ema and 5ema.

ADF FOODS-2022-2023

Date	Close	3ema	5ema	Macd
September-22	733.60	244.53	736.60	492.07
October-22	711.15	237.05	718.34	481.29
November-22	828.10	276.03	739.49	463.46
December-22	779.95	259.98	755.67	495.69
January-23	762.95	254.32	763.15	508.83
February-23	731.25	243.75	762.68	518.93
March-23	743.80	247.93	769.21	521.28
April-23	746.45	248.82	752.88	504.06
May-23	885.15	295.05	773.92	478.87
June-23	936.20	312.07	808.57	496.50
July-23	1040.65	346.88	870.45	523.57
July-23	1040.65	346.88	929.82	582.94

INTERPRETATION:-

- The 3ema and 5ema were both moving upwards in the beginning of 2023, which indicates that the trend was bullish.

- The stock price has been declining since May 2023, and is currently trading below the 3ema and 5ema.

Overall, the stock price data for ADF FOODS is bearish.

HYPOTHEIS TESTING

HYPOTHESIS

H0 there is no significance relation between the moving averages and stockprices. (Rejected)

Table1

Date	ADFFOODS	Dabur India Limited	ITCINDIALTD
8/1/2018	macd	macd	macd
9/1/2018			
10/1/2018			
11/1/2018			
12/1/2018			
1/1/2019	155.0767	282.48	199.1467
2/1/2019	159.4333	271.1267	191.9067
3/1/2019	165.8867	275.2233	188.4333
4/1/2019	170.8067	289.7833	184.7967
5/1/2019	163.9333	291.15	186.54
6/1/2019	153.04	284.9267	193.52
7/1/2019	165.9133	274.78	194.1267
8/1/2019	176.9433	263.81	194.1733
9/1/2019	178.4133	264.36	192.0367
10/1/2019	177.7667	274.7067	179.0033
11/1/2019	172.57	283.0067	175.5567
12/1/2019	174.3733	295.6767	173.8167
1/1/2020	183.4367	302.3	170.2167
2/1/2020	195.5967	299.24	168.9667
3/1/2020	202.3367	308.8933	169.04
4/1/2020	209.9633	321.8633	160.4667
5/1/2020	179.0667	314.82	144.1467
6/1/2020	150.01	324.0467	130.9767
7/1/2020	143.7567	318.2533	123.7767
8/1/2020	143.5267	305.8767	123.2633
9/1/2020	174.9033	323.77	128.16
10/1/2020	194.7433	316.0367	132.5567
11/1/2020	224.13	324.7367	128.2867
12/1/2020	242.3333	335.39	118.62
1/1/2021	242.5633	328.08	116.4733
2/1/2021	301.87	342.5533	120.82
3/1/2021	321.2367	344.88	127.05
4/1/2021	393.93	338.2233	132.8167

5/1/2021	473.8933	346.69	139.9067
6/1/2021	527.1433	347.18	136.76
7/1/2021	611.15	348.5867	141.2833
8/1/2021	627.05	357.4567	140.7533
9/1/2021	643.22	366.7233	137.1967
10/1/2021	603.9433	384.0067	135.6233
11/1/2021	586.2967	403.4867	141.26
12/1/2021	578.79	405.6933	145.6333
1/1/2022	560.0767	406.53	149.2867
2/1/2022	553.42	404.0133	150.35
3/1/2022	567.2967	384.4067	147.74
4/1/2022	539.7133	383.5267	141.63
5/1/2022	536.07	369.0433	146.3433
6/1/2022	520.2767	369.4	153.1633
7/1/2022	518.4067	368.9233	162.8733
8/1/2022	518.9933	343.69	170.4633
9/1/2022	499.62	353.3367	178.6167
10/1/2022	492.0667	360.1367	189.2467
11/1/2022	481.29	373.36	199.3567
12/1/2022	463.4567	380.6233	215.5567
1/1/2023	495.6867	385.06	224.0733
2/1/2023	508.8333	381.1233	223.51
3/1/2023	518.93	381.4367	224.2933
4/1/2023	521.2767	375.3767	228.9867
5/1/2023	504.0633	368.2867	232.08
6/1/2023	478.87	359.5767	248.22
7/1/2023	496.5033	356.7667	266.0367
7/7/2023	523.5667	364.9367	278.7767

FINDINGS

Overall, the stock price data for ADF FOODS is bullish. The stock price has been trending upwards and the technical indicators are all pointing to further gains.

Overall, the stock price data for ADF FOODS is bearish. The stock price has been trending downwards and the technical indicators are all pointing to further losses.

Overall, the stock price data for DABUR INDIA LIMITED is be arise. The stock price has been trending downwards and the technical indicators are all pointing to further losses.

Overall, the stock price data for DABUR INDIA LIMITED is mixed. such as the declining Macd and the recent volatility. Investors should carefully consider the risks and rewards before investing in DABUR INDIA LIMITED stock.

Overall, the stock price data for ITC is bearish. The stock price has been trending downwards and the technical indicators are all pointing to further losses.

Overall, the stock price data for ITC is mixed. There are some positive signs, such as the upward trend in the 3ema and 5ema in the beginning of 2021. However, there are also some negative signs, such as the declining Mac and the recent volatility. Investors should carefully consider the risks

and rewards before investing in ITC stock.

Overall, the stock price data for ITC is mixed. There are some positive signs, such as the upward trend in the 3ema and 5ema in the beginning of 2022. Overall, the stock price data for ITC is bullish. The stock price has been trending upwards and the technical indicators are all pointing to further gains.

CONCLUSION

Deep in India, there is a segment of the processing market that focuses on food feed, processed natural products and vegetables, empty and partially empty products, refreshments, perspective, chicken products, different meats, and red meat products. This market is spread out using soda pops, a variety of beverages, breakfast oats, bread, rolls, chocolate retailers, a significant number of chances are likely available at any one moment. Comparing the considerable style program swap with alternative methods of increasing one's hazards in the cash-connected market sectors has shown promise in the short term.

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