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Evaluation of Forecasting Methods from Selected Stock Market Returns

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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 modelsto determine their accuracyand reliabilityin forecasting future stockprices or market trends. Different methods, ranging from traditional statistical models like ARIMA (AutoregressiveIntegratedMoving Average) andmovingaveragesto morecomplexmachine learning algorithms such as neural networks and decision trees, are utilized to predict market behavior.

Thisevaluationisnot just about selectingthe methodwiththehighest predictiveaccuracybut also involves considering factors such as the volatility of the market, the time horizon of predictions, and the specific characteristics of the stocks or indices being analyzed. For instance,high-frequencytradingrequiresextremelyaccurateshort-termforecasts,while long- term investors might prioritize models that capture broader market trends over time.

Moreover,theeffectivenessofthese methodscan varysignificantly based onthedata's nature and the market conditions. Thus, continuous back-testing and refinement ofthese models are crucial to adapt to changing market dynamics. 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.

REVIEWOFLITERATURE

ChengZhao(2023)Predictingstockpricesiscrucialforstockmarketinvesting.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. More datais needed due to the linkageeffect inthestockmarket, wherestockvaluesareimpactedbyrelatedstocks.Industry categorization data from third-party sources provides most stock connection information, however it is sometimes imprecise and delayed. This work presents a time-series relational model (TSRM) that blends time and relationship data. TSRM uses stock transaction data to automaticallyclassifystocksanddeterminestocklinkagesusingaK-meansalgorithm. LSTM time series and graph convolutional 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 surveyhasexaminedfeatureselectionandextractionmethods.Thissurveyanalyzes32feature study-MLresearchstudies in stock market applications. WesystematicallysearchScopusand Web of Science for 2011–2022 papers. 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, correlation criteria, random forest, principal componentanalysis, and auto encoder are the most popular feature selection and extraction methods with the greatest forecast accuracy.

Mostafa Shabani (2023) Cross-correlation analysis is a powerful tool for understanding the mutualdynamics oftime 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. We adopt a deep learning framework for methodologically addressing the prediction of the synchronization state based on features extracted from dynamically sub- sampledcross recurrenceplots.Weprovideextensiveexperiments on several stocks,major constituentsoftheS&P100 index, to empiricallyvalidateourapproach. We findthatthetask of predicting the state of synchronization of two-time series is in general rather difficult, but for certain pairs of stocks attainable with very satisfactory performance (84% F1-score, on average).

Sudeepa Das (2022) Stock indexprice forecasting helps investors and financialinvestigators makedecisionswithmaximumgainand minimalrisk. Tosucceed, apowerfulenginethat 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.PGCSAmethodimprovesstandardELMbyachievingsuitableweightsandbiases. 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 mostlyusedtopredict capitalmarket pricesinfinance.Thisarticleusedclassicalandmachine 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 modelusing 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.

AlessioStaffini(2022) Stockmarket pricesareknowntobeveryvolatileandnoisy, andtheir accurate forecasting is a challenging problem. Traditionally, both linear and non-linear methods (such as ARIMA and LSTM) have been proposed and successfully applied to stock market prediction, but there is roomto develop models that further reduce the forecast error. Inthis paper, weintroduce aDeepConvolutionalGenerative AdversarialNetwork(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 diBorsa), the benchmark stock market index for the Italian national stockexchange.Byconductingbothsingle-stepandmulti-stepforecasting,weobservethatour 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.

Rajat Patil (2021) In economics, business and technology, predictive analysis of the time seriesdataisanessentialaspect.Traditionally,somanymethodsexisttoefficientlypredictthe next lag oftime series data. The main aimofthe research is to investigatethe functionalityof thestockexchange inthe improvement oftheIndianeconomyutilizingthetime seriesdataof various industrial sectors from the years 2000 to 2020 and to conduct the comparative time series analysis of machine learning models like ARIMA, ARIMAX and recurrent neural network model like LSTM. The results of the research show that ARIMAX model has outperformed the ARIMA and LSTM models. Also, from this analysis, it can be understood that the performance of the LSTM model is better for the larger datasets. In addition, it was observed that increasing the numberofepochsdoesnot impact the performance ofthe LSTM modeland showed a purelyrandombehavior. Theaddition ofexogenous featuresto the Auto ARIMA model is commonly called as ARIMAX model. This addition ofexogenous features like date time features to the stock price data improvises the performance of the ARIMAX model.

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. Fixed-pricestrategies,whichhavebeenappliedinDSAforpricingdecisions,aregenerallyinefficient at maximizing the potential profit of the service provider, 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,the time-series forecasting method is asuitablepricingsolutionforDSA,asitimprovesthepricingdecisionbymodelingthechanges

in the environmental factors and audience attention level toward signage for optimal pricing. However, it is difficult to determine an optimal price forecasting model for DSA with the increasingnumberofavailabletime-seriesforecastingmodelsinrecent years.Basedonthe84 research articles reviewed, the data characteristics analysis in terms of linearity, stationarity, 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, TCSand ITC)Companiesaretaken Securityproductsselected 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 marketconditionsarelacking.Addressingthesegapscouldenhanceforecastingreliabilityand 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.

To analyze the volatility and future growth of securities in national stock exchange.

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 marketplaces over a considerable amount oftime onprices, volumes, and economic variables relatedtothestockmarket.Thisdatawillbesubjectedtoavarietyofforecastingmodels,which will include hybrid approaches, machine learning techniques, and conventional statistical methods. Metricsincludingaccuracy, meanabsoluteerror(MAE),androotmeansquareerror (RMSE) will be used to evaluatethesemodels'performance.Theadvantagesanddisadvantages 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

ADFFOODS-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:-

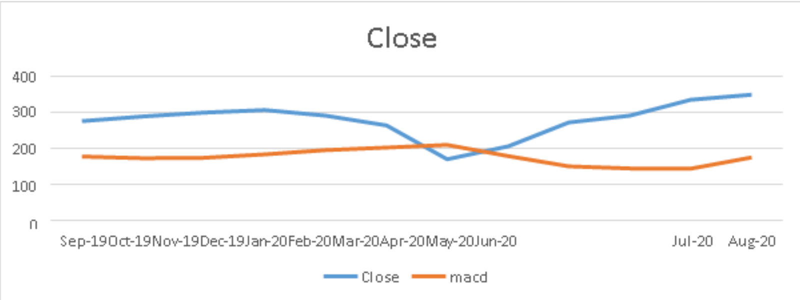
- Thestockpricestartedat216.70inSeptember2018andreachedahighof293.10inMay2019.

- The3emaand5emawerebothmovingupwards,whichindicatesthatthetrendwasbullish.
- TheMacdwasalsomovingupwards,whichconfirmsthebullishtrend.
- Thestockpriceexperiencedapullbackin July2019,butithassincerecoveredandiscurrently trading above the 3ema and 5ema.

Overall, the stock price data for ADF FOODSisbullish. The stock price has been trendingupwards and the technical indicators are all pointing to further gains.

ADFFOODS-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



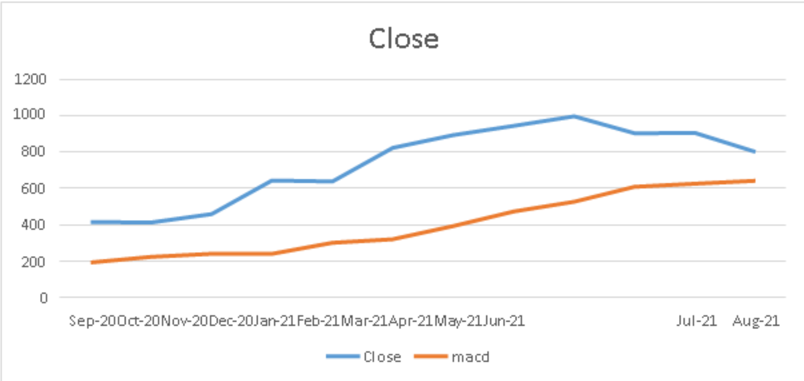
INTERPRETATION:-

- The stock price started at 275.95 in September 2019 and reached a high of 350.30 in August 2020.
- The3emaand5emawerebothmovingupwards,whichindicatesthatthetrendwas bullish
- TheMacdwasalsomovingupwards,whichconfirmsthebullishtrend.
- ThestockpriceexperiencedasharpdeclineinMarch2020,whichwaslikelyduetothe COVID-19 pandemic.
- Thestockpricehassincerecoveredandiscurrentlytradingabovethe3emaand5ema.

ADFFOODS-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



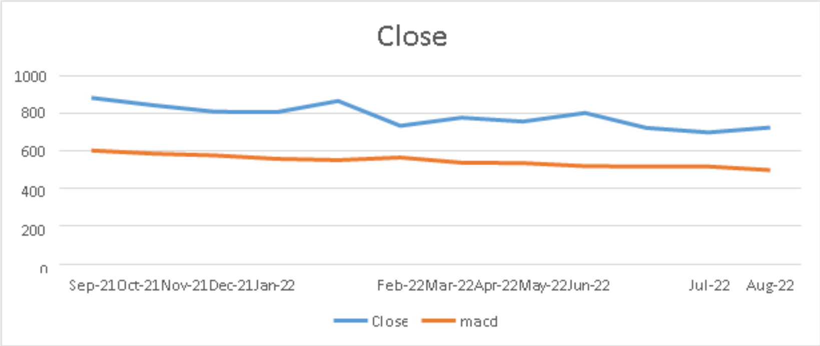
INTERPRETATION:-

- Thestockpricestartedat417.65inSeptember2020andreachedahighof996.65inMay2021.
- The3emaand5emawerebothmovingupwards,whichindicatesthatthetrendwas bullish.
- TheMacdwasalsomovingupwards,whichconfirmsthebullishtrend.
- ThestockpriceexperiencedapullbackinJune2021,butithassincerecoveredandiscurrently trading above the 3ema and 5ema.

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

ADFFOODS-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

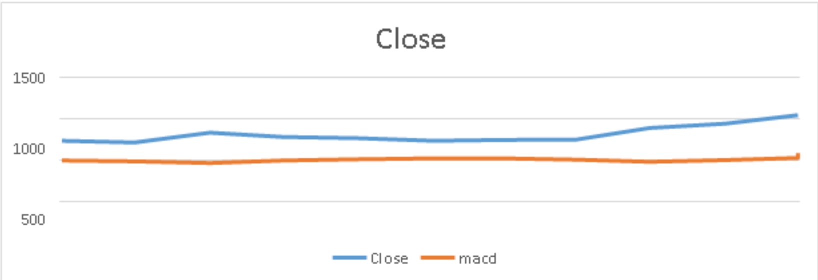


INTERPRETATION:-

- The stock price started at 882.65 in September 2021 and reached a high of865.20 in January 2022.
- The3emaand5emawerebothmovingupwardsinthebeginningof2022,whichindicatesthat the trend was bullish.
- However,theMacdstartedtodeclineinJanuary2022,whichindicatesthatthetrendwas starting to become bearish.
- ThestockpricehasbeendecliningsinceJanuary2022,andiscurrentlytradingbelowthe3ema and 5ema.

ADFFOODS-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:-

- Thestock pricestartedat733.60 in September2022andreachedahigh of 1040.65 in July 2023.
- The3emaand5emawerebothmovingupwardsinthebeginningof2023,whichindicatesthat the trend was bullish.
- However,theMacdstartedtodecline inMay2023,whichindicatesthatthetrendwasstarting to become bearish.
- 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. The stock price has been trendingdownwards and the technical indicators are all pointing to further losses.

HYPOTHEIS TESTING

HYPOTHESIS

H0thereisnosignificancerelationbetweenthemovingaveragesandstockprices. (Rejected)

Date	ADFFOODS	DaburIndiaLimited	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

Table1

Inference:- H0 there is no significance relation between the moving averages and stock prices. We can reject the hypothesis means there is significance relation between the moving averages and stock price. From the above analysis about time series of moving average analysis highly influence on forecasting of security price.

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,thestockpricedataforDABURINDIALIMITEDisbearish.Thestockprice 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. There are some positivesigns,suchastheupwardtrendinthe3emaand5ema.However,therearealso some negative signs, 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 alsosomenegativesigns,suchasthedecliningMacdandtherecentvolatility.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. However, there are alsosomenegativesigns,suchasthedecliningMacdandtherecentvolatility.Investors should carefully consider the risks and rewards before investing in ITC stock.

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.

SUGGESTIONS

MacD provides an incredible amount of information in a clear and concise format. The MACDoscillatesbothaboveand belowa middlezerocollection,whichisagreat indicatorof the dominant phenomena' course and signaling

Whenthe MACD type crosses above the middle type, there will be anuptrend. WhentheMACDtypecrossesbelowthe middletype,therewillbeadownturn.

Thesignaltype maybeused bysomeshort-termtradersto initiatebuysignalswhenthe MACD type crosses over it.

If the MACD type goes below the signal type, sell the indicators. Since the short-term techniquegeneratesa lotoffalsesigns, it maynotbetrustworthy.Instead,considertherole ontheMACDtyperelativeto thezero typeasan indicationthat theinventoryhas begunto trend.

Each and every bar in the histogram represents the significant difference between the two shifting averages for that specific day. Since you can visually see how quickly the histogram barsareclosing insideordivergingoutofthezerokinds, youdo not needto employthe bring about type within the histogram:

CONCLUSION

Deep in India, thereisasegmentoftheprocessingmarketthatfocusesonfoodfeed, 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, consumable oils, and malt protein-rich products.Understanding how to see opportunities and developstrategiestoseizethemisoneofthemanykeystobeginningandgrowingasuccessful food processing company. The best tool for breaking on inventories for brokers in securities exchangeistheMACDgadget.Naturally,giventhatdifferentstocksarealwaysbeingreplaced in the market, a significant number of chances are likely available at any one moment. Comparing the considerable style programswap with alternative methods of increasing one's hazardsinthecash-connectedmarketsectorshasshownpromiseintheshortterm.

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