Exchange Stock Price Prediction using Time Series data: A Survey

Hamid Ghous[1], Mubasher H Malik[2], Ayesha Mahrukh[3], Abdul Mueed Zaffar[4]

[1] Institute of Southern Punjab, Multan, Pakistan. Email: hamidghous@isp.edu.au
[2] Institute of Southern Punjab, Multan, Pakistan.
[3] Institute of Southern Punjab, Multan, Pakistan.
[4] Institute of Southern Punjab, Multan, Pakistan.

ARTICLE INFO	ABSTRACT
	Stocks, which are ownership shares in the company, can be issued and traded on the platform known as a stock exchange by publicly traded companies. A centralized marketplace is provided by a stock exchange where stocks can be traded by buyers and sellers coming together, thereby ensuring liquidity and price transparency. Large studies have been conducted for a long time in regions such as foreign exchange, stock prices, and weather reviews where time series forecasting information has been comprised. In our research work, we will use time series data because time series allows us to compare what elements have an effect on certain variables from time to time. The primary goal of this review paper is to provide a comprehensive overview of the research conducted by various scholars on predicting stock market prices using time series data. Evaluating time series data can provide valuable insights into the changes in a particular asset, security, or financial variable over time. Forecasting techniques using time series analysis are employed in both fundamental and technical analysis.

Corresponding Author's Email: hamidghous@isp.edu.au

1. Introduction

The stock marketplace is a market in which securities including shares and bonds are offered and sold. Exchanges often function as ongoing auction markets, with buyers and sellers completing trades through public protests at central venues such as stock exchanges or through electronic trading platforms. It is a market that connects savers and borrowers, and as a financial market, it transfers capital and money from those who have excess cash to those who need funds and investments. Investors are generally referred to as profit-making entities and business and deficit units and connect borrowers and lenders. Large studies have been conducted for a long time in regions such as foreign exchange, stock prices, and weather reviews where time series forecasting information has been comprised. In the starting, issues with economic evaluation and prediction had been solved through statistical models and methods. Over the past few years, a plethora of learning models based on artificial neural networks have emerged to tackle financial data issues and deliver accurate results for predicting future trends and prices. Modern-day time series prediction consists of the prediction of exchange rates.

This section covers the topic of a stock exchange, highlighting both its advantages and disadvantages. Additionally, the potential impact of stock exchange prediction on the economic growth of various countries is examined. Furthermore, it emphasizes the impact of the financial market, big data analysis, and time series data. The stock market investment provides a safe and regulated environment in which investors can confidently share their trades, which helps them increase versatility, higher return in a shorter period, and higher liquidity. On the other hand, the stock market has some cons which may lead to low margins, high brokerage, impulsive investment, time consumption, and lack of knowledge may lead to a higher risk of losses. Financial markets have a tremendous influence on a country's economy since they are the engine that drives it. A greater focus has been placed on stock trading recently. One popular approach to attempt stock market forecasting is to model conventional financial data sources using deep

learning and machine learning methods. Deep learning and machine learning models are often trained on technical indications, macroeconomic factors, and fundamental indicators to forecast future stock performance.

However, with the increasing interest in big data, deep learning, and machine techniques, the popularity of monitoring the stock market using new analytical techniques is growing. Modern stock trading involves the complex use of technology. As traders demand information to maximize their profits, the race to obtain relevant information is very interesting. Therefore, it is desirable to support financial analysts by making financial data available using modern modeling techniques such as financial language models. Tools and modeling techniques are being sought by investors to increase their profits and reduce risks, but the stock market is known to be a difficult domain to predict. The rational goal of an organization is to provide value. With hundreds of millions of events occurring every day and stored in large volumes, the focus on deriving value from data is growing. Tools that interact with big data are of great interest to many organizations because modern modeling technology makes it possible to predict behavior and events. Because of this, data is considered one of the most valuable commodities in automated decision-making systems. These technologies are used by several businesses across numerous sectors. Financial professionals employ a variety of data to conduct market monitoring and predictive research since big data has grown to be a significant component of the financial sector.

In addition, the financial industry uses data and technology to enable efficient and accurate information processing. As a result, financial applications such as risk analysis, real-time analytics, fraud detection, algorithmic trading, and consumer analytics were born. However, a larger number of potential use cases are still largely uncharted due to the growing amount of unstructured data such as text data. On the other hand, financial institutions and industries are discovering the value of text data for applications such as chatbots for customer engagement and text analytics for market insights. Extracting and structuring unstructured economic text is an undertaking task, yet an essential step in understanding statistics profits. Time series analysis can offer valuable insights into the behavior of a particular asset, security, or financial variable over time. Additionally, it can be utilized to investigate the relationship between changes in a specific data factor and fluctuations in other variables over the same period.

A set of observations obtained by making repeated measurements over time is known as a time series statistic. When factors are plotted on a graph, time is always represented on one of the axes. Subsets of data tracked over the years are referred to as time series metrics. For instance, a metric should check the number of shares that were bought in a trade from a certain point to the next. Time series information is anywhere due to the fact time is part of the entire that is observable. With our global surroundings becoming more instrumented, sensors and systems constantly transmit a steady flow of time series data. Time series data can also comprise server metrics, overall software program performance monitoring, activity, sensor records, network data, clicks, and various other types of analytical data.

The stock market promotes investment and ensures price transparency and liquidity. The elevating of capital permits businesses to develop their organizations. The stock market exists to serve the wider economy. Somehow the stock market provides a ready market for buying and selling depending. The stock market promotes investment and ensures price transparency and liquidity. Predicting stock market trends and prices plays a crucial role in determining the future value of a company's shares and other financial transactions in the market. Accurate predictions of stock prices can have a positive impact on the economy of a country. It helps investors know which factor influences the price of stock more. Stock market prediction helps generate an increase in the sales rate, GDP, and earnings of the corporation. In the next section, we will discuss the literature review related to stock exchange price prediction which is further divided into subsections. However, section three discusses the review based outcomes and section four concluded the research.

2. Literature Review

In the past twenty years, numerous artificial neural network-based learning models have been introduced to address financial data issues and achieve precise outcomes in forecasting future prices. The contemporary time series prediction also encompasses the prediction of exchange rates. The following are some of the works of previous studies regarding stock

exchange forecasting price prediction. The review is categorized based on literature using machine learning methods and the literature related to deep learning methods.

2.1. Deep Learning

T. H. H. Aldhyani and A. Alzahrani (2022), Stock market prices are evaluated for substructure modeling and prediction. The dataset for this paper was obtained from Tesla, Inc. and Apple, Inc., and USD was used as the currency. The Tesla dataset for period of 4 August 2014-17 August 2017. The Apple dataset for period of 3 January 2010-28 February 2020, from which 70% as a training set, and 30% as a testing set. The pre-processing technique used was Normalization using Min-Max normalization. Feature extraction was conducted using filtering techniques. Further CNN was performed to capture topology. The methodology sector included various methods such as CNN-LSTM, RMSE, MSE, NRMSE, and R. The results showed that Tesla, Inc. CNN-LSTM 98.37%, LSTM 97.7%; Apple, Inc. CNN-LSTM 99.48%, LSTM 99.25% which means CNN-LSTM is better than LSTM. In future work, improved deep learning techniques can be utilized to analyze the accuracy of the presented work.

Suphawan, Kardkasem, and Chaisee (2022b) bring forward a Gaussian process regression model for forecasting the stock exchange of Thailand. The dataset was obtained from Thailand's stock exchange, divided into 2 sets before and after covid-19 (5 January 2015 to 30 June 2020) and (26 May 2020 to 30 June 2020). The pro-processing techniques were the Gaussian process, regression, and Max scaling. The methodology models were ANN, RNN, and GPR. The results showed that GPR performs better than ANN and RNN. Alaameri and Faihan (2022a)It is proposed to forecast the profits of banks that are listed on the Iraq Stock Exchange. The implementation was conducted on 12 Iraqi companies between the period of 2004 -2019. The smoothing function was used to process data including feature extraction through RMSE and MAPE. The methodology used was LSTM and NAR. It was found that NAR outperformed LSTM in predicting forecasted profits for the banks listed on the Iraq stock exchange.

Mohamed M. Mostafa (2010)came up with forecasting stock exchange movement using neural networks. The dataset used of all listed companies on KSE from 17 November 2001 - 30 November 2003,612 data points in time series. The pre-processing technique used was a multilayer perceptron. Feature extracted through Mean square error. The methodology used was MLP, Generalized regression neural network. The results indicate that neural network models are effective in predicting stock market movements with satisfactory performance. Wu, Liu, Zou, and Weng (2022a)recommended stock price prediction on multiple data sources. The dataset used was a technical indicator, historical data, non-traditional data sources, and five stock market set-down companies from EastMoney2351 articles,33500 forum posts in 3377 transactions from 1 July 2017 to 30 April 2020. The pre-processing techniques used were clearing, filtering, text data, document labeling, text classification, image classification, and segmentation. The feature extraction included skip-gram, embedding layer, 3 convolutional layers, and dropout methods. The methodology used is sentiment index, LSTM prediction model, ATT0 LSTM, MAE, MAPE, and RMSE. The findings indicated that the prediction of stock prices involved the integration of technical indicators and investor sentiment.

Mustafa, Bajwa, and Iqbal (2022a)preferred a graph-based approach in the stock market. The dataset was obtained from various sources, including social media, stock descriptions documents, and historical return data, using different graph approaches. The preprocessing was sampling, lagging, window size, and threshold. The feature extraction used was Pearson's 13 correlation coefficient. The methodology used were ARMA, FIEGARCH, LSTM, ARFIMA, SM, ANN, CNN, MAPE, and MSE. Graph-based approaches are useful in improving portfolio performance, as demonstrated by the results obtained in the study. Fleischer, Von Laszewski, Theran, and Bautista (2022) proposed a time series analysis to study the changes in cryptocurrency prices. The dataset included a CSV file of cryptocurrency price historical records of the Yahoo page for EOS-USD. The pre-processing technique used was normalization. The feature extraction used was the LSTM well dropout layer to prevent overfitting. The methodology included LSTM, and Root means square error. The results showed that the values of the experiment affect each other as well.

Albahli et al. (2022a)The study proposed the use of a Dense-Net model along with an autoencoder for stock market prediction. The dataset of 10 years of Yahoo finance data was

2640 data points. The pre-processing used was the linear regression approach. The feature extraction was done using dimensionality reduction autoencoder and data point labeling. The methodology used were MA, stock technical indicators, WMA, EA, RSI, and CMO.HMA, DMI, PL, CCI, CMF, SO, MD, RCI, BB, Evaluation parameters. The proposed method had the best performance among all others, PCT had the highest values. The results of this paper were remarkable. Zahra, Chishti, Baba, and Wu (2022a)presented data mining-based and fuzzy logic intelligence systems. The dataset of Whois DS (Malicious data) 6321 Covid-19 related malicious data. The data is processed with filtering and features are extracted with the usage of fuzzy logic. The methodology was the data mining algorithms. The evaluation results showed the validity of the paper approach.

Wang, Wang, Fang, and Niu (2016)A study was conducted using Elman Recurrent Random Neural Network for the prediction of financial time series data. Different stock indices such as the shanghai stock exchange (16/03/2006-19/03/2014), The TWSE were studied from (09/02/2006 - 9/03/2014). Korean Stock price index (20/02/2006- 19/03/2014) and NIKKEI 255 index (27/01/2006-19/03/2014). The Min-Max normalization is used as a pre-processing technique. Further data was extracted using the Drift function, volatility function, and standard Brownian motion. The methods used were BPNN, STNN, ERNN, performance measures, and a CID analyzer for time series. It was shown by the study that the proposed model had the benefit of better precision in forecasting, with the following accuracies: SEE - 2320.2, TWSE - 10830, KOSPI - 2551.0, Nikkei225 - 32895.

Xiao and Su (2022)the research was conducted based on deep learning using stock market time series prediction. The dataset used was stock samples (2010-2019) New York stock exchange (1 January 2010 - 31 December 2019)2519 sets of data with 90% training set and 10 % testing set. The pre-processing was done using sampling. The features were extracted using the ACF graph and PACF graph. The methodology used was the ARIMA model LSTM, RNN, SI model, and Evaluation matrices. The results showed that a lower loss function was achieved by both ARIMA and LSTM. It was found that ARIMA was more feasible for predicting the correlation coefficient of portfolio optimization. Teng, Wang, Zhang, Lan, and Luo (2020) proposed enhancing stock price trend prediction. The dataset of 50 stocks among 10 sectors from 2007-2016 was obtained. The data was pre-processed using Enhancement and augmentation methods. The feature extraction was done using a transformation technique (on high frequency). The methodology used was LSTM, Evaluation metrics. The result showed that based on LSTM model augmentation of high-frequency data is 56%. So, the result shows that the stock price prediction performance is boosted by the proposed data augmentation method.

Yujun, Yimei, and Jianhua (2020a)using LSTM a hybrid prediction method for the stock price was shown in the study. The dataset included is automatically generated from the computer which is artificially simulated, as well as experimental data consisting from Yahoo is in index form of real-world stock. Finance and 5 stock indexes include five daily properties. The data was processed by removing noise from the data. The feature extraction was done using logarithmic. The methodology includes LSTM, SVR, BARDR, and KNR, proposed methods were LSTM-EMD and evaluation metrics. Some unwanted consequences on time series results were observed with the proposed method in this paper.

Ahmed, Hassan, and Mstafa (2022) forecasting time series data using deep learning techniques were put forward in the paper. The dataset was of 60 papers from the last 3 years mostly 2021,26 articles most popular for ANN, LSTM, and TCNN. The pre-processing technique used is splitting of data and segmentation. The feature extraction was done using a validation set. The methodology was implemented by Deep learning model, ANN, LSTM, TCNN, and Evaluation metrics. It was concluded that a variety of papers exploded. Appropriate guidance regarding the use of time series data was helpful.

Jung and Choi (2021b)worked over deep learning autoencoder LSTM techniques. 2520 daily time series FXVIX from January 2010-December 2019, data divided into subsets 2010-2015,2016, and 2017-2019 was used as the dataset. The pre-processing technique used was Min-Max normalization and denoising. The feature extraction was performed by cross-validation technique. The methodology conducted was LSTM, RNN, autoencoder-LSTM, and error measures. The results indicated that predicting FXVIX autoencoder -LSTM is better than LSTM with accuracy LSTM MAPE:7.8089% and Autoencoder-MAPE:8.7721%.

Table 1: Metadata for Deep Learning

Reference	Dataset	Pre-processing	Feature Extraction	Methodology	Results
T. H. Aldhyani and A. Alzahrani (2022)	Tesla, Inc 4 Aug 2014 - 17 Aug 2017 Apple, Inc 3 Jan 2010 - 28 Feb 2020	Normalization(Min-Max Normalization)	CNN is to perform feature extraction to capture topology Filtering	(LSTM) (CNN-LTSM) (MSE) (RMSE) (NRMSE) Pearson's correlation(R)	Model: CNN-LSTM R (99.73%) Model: LSTM R(99.25%) (Tesla: R-squared = 98.37%; Apple: R-squared = 99.48%).
Suphawan, Kardkasem, and Chaisee (2022a)	Stock Exchange of Thailand(5 Jan 2015 -30 June 2020 & 26May 2020-30 June 2020)before and after the covid outbreak	Min-Max scaling Normalization	Guassian process regression	ANN, RNN, GPR	GPR performs better than other ANN and RNN methods
Alaameri and Faihan (2022b)	12 Iraqi banks Dataset period: 2004-2019	Smoothing Function	RMSE MAPE	LSTM NAR	NAR is better than LSTM for the problem of forecast profit
Mohamed M Mostafa (2010)	Companies listed on KSE 17 Nov 2001 -30 Nov 2003 & 612 data points in time series	Multilayer perceptron	Mean Square error	MLP, Generalized regression neural network	model is useable for forecasting stock exchange movement as it shows satisfactory performance
Wu, Liu, Zou, and Weng (2022b)	Five listed companies of stock from EastMoney.com Dataset period:1 July 2017-30 April 2020 Test Set: 1 Jan 2020- 30 April 2020	Clearing, filtering testing data, document labeling, segmentation, text classification, Image classification	Convolutional Kernel & Dropout method	LSTM prediction model, ATT LSTM, MAE, MSE, RMSE, Sentiment Index	The proposed method incorporated investor sentiment and technical indicators into the stock price prediction. The paper still needs further improvement
Mustafa, Bajwa, and Iqbal (2022b)	Pattern mining in big IOT for malware detection	, Fuzzy logical relationship, Evaluation sets	Fuzzy least square approach	FGARCH model GARCH model	FGARCH shows 90% accuracy GARCH shows 88% accuracy
Fleischer et al. (2022)	CSF file of Cryptocurrency price historical records YAHOO page for EOS-USD	Normalization	LSTM well dropout layer to prevent outfitting	LSTM, ROOT MEAN Square Error	Shows that the values of the experiment affect each other
Albahli et al. (2022b)	10 years of Yahoo finance data,2640 data points	Linear regression approach	Dimensionality Reduction autoencoder data point labeling threshold	MA, WMA, EA, RSI, CMO, HMA, DMI, PL, CCI, CMF, SO, MD, RCI, BB, Evaluation Parameters	PCT had the highest values. The result of this paper was remarkable
Zahra, Chishti, Baba, and Wu (2022b)	6321 Covid-19-related malicious data	Filtering	Fuzzy logic	Data mining algorithms	The evaluation results show the validity of the paper's approach
Wang et al. (2016)	(SSE) 16/03/2006-19/03/2014 (TWSE)09/03/2006-19/03/2014(KOSPI) 20/02/2006-19/03/2014 Nikkei 225 27/01/2006-19/03/2014	Normalization Min-Max	ST-ERNN Gradient descent method Drift function Standard Brownian motion	BPNN,STNN,ERNN,Performance measures (RMSE,MAE,MAPE,MAPE(100)) CID analyser for kine series	CID and MCID gave clarification SEE: 1659.9 TWSE: 6158.1 KOSPI: 1006.0 Nikkie225: 25421
Xiao and Su (2022)	Stock samples from 2010-2019 NewYork Stock exchange 1 Jan 2010 to Dec 31 2019 2519 sets of date	Sampling	ACF graph,PACF graph	The lesser loss function was observed for both ARIMA and LSTM models, and it was found that ARIMA LSTM can be used for predicting the correlation coefficient of	The feasibility of predicting the correlation coefficient of portfolio optimization using ARIMA LSTM was demonstrated.

					portfolio optimization
Teng et al. (2020)	50 stocks among 10 sectors from 2007- 2016	Enhancement	Transformation techniques	Augmentation method, MSE, MAE, LSTM model	Augmentation original time series is 97%. High-frequency data: 56%
Yujun, Yimei, and Jianhua (2020b)	real-world stock index data from Yahoo finance 5 stock indexes include fine daily properties	Removing noise data	logarithmic	LSTM,SVR,BARDR,KNR Proposed Methods: 1-LSTM-EMD 2-LSTM-EEMD Evaluation metrics	The proposed method in this paper has some unexpected effects on the experimental results of time series
Ahmed et al. (2022)	60 paper from last three years mostly 2021 26 articles most popular for,LSTM,TCNN	Splitting data	Validation set	,LSTM,TCNN, Evaluation set Classification Metrics: Regression metrics ,profit analysis,Significance analysis	Variety of papers exploredAppropriate guidance regarding the use of time series data is helpful
Jung and Choi (2021a)	2520 daily time series FXVIX January 2010-Dec 2019 Data divided into subsets 2010 to2015,2016 and 2017-2019	Min-Max normalization ,Denoising	Cross -Validation techniques	LSTM,RNN process,Autoencoder-LSTM,Error Measures	LSTM Predicting FXVIX autoencoder-LSTM is better than LSTM LSTM Mape= 7.8089% Autoencoder MAPE =8.7721%

2.2. Machine Learning

The field of machine learning is one of the roots of artificial intelligence that focuses on machines imitating intelligent human behavior. It involves the use of AI frameworks to perform complex tasks like how humans would approach them. Zhou, Xu, and Zhao (2018)suggested tales of emotion. The dataset consists of 3 million investors on Weibo and public stock-relevant 10 million tweets, covering the period (1 Dec 2014 to 7 Dec 2015), and exhibiting the classification of 5 emotions, including sadness, anger, joy, repulse, and fear. The pre-processing technique used was Naive Bayes Classifier filtering. Feature extraction was done by manual selection using keyboards (Emotion classification and online emotion). The methodology used was SVM-ER, SVM-MR K means Logistic Regression. The results showed SVM-ES is better.

Fataliyev, Chivukula, Prasad, and Liu (2021)presented text-based stock market analysis. The dataset was taken from different social media platforms whereas textual data includes financial, general news, corporate, announcements, blogging, and microblogging websites and textual content includes news, financial blogs, social media, and discussion boards. The pre-processing techniques included a bag of words, word embedding, event embedding, paragraph vectors, aspect-based sentiments, and LDA. The features were extracted through event extraction, sentiment extraction, extracting sentence level and document level sentiments. The methodology implemented is statistical techniques, machine learning, deep learning Linear regression, GARCH, ARMA, SVR, Naive Bayes, LSTM, and RCNN. The results showed that Hybrid analysis models have shown great potential and can usually lead to better results than conventional methods.

RINGMU and OUMAR (2022a)In the New York stock exchange forecasting of stock prices was proposed. The dataset of 59 industries of NYSE which include the gas and oil sector from the period of January 2012 to December 2019 was used. Convenient sampling and salient dynamic features were used as pre-processing techniques and feature extraction. The methodology implemented was different models such as the ARIMA and Box Jenkin 1973 methods. It was shown by the results that a random walk is followed by the stock prices in NYSE depending upon the consideration of before and after difference in the standard errors. A. W. V. M. Amunugama, H. T. K. Abeysundara, and U. N. B. Dissanayaka (2022)initiated ARIMA and FBMAP approaches. The dataset with 50 trading days, from the period of January 2015 to June 2019 for 20 companies from the central bank of Sri Lanka's annual report. The pre-processing technique used was the Chi-Square test, autocorrelation test, and Runs test. The feature extraction used the RMSE, MAPE, and Box Jenkins test. Methodology 11 included the ARIMA model, ARCH model, and FBMAP. The results showed that FBMAP is more suitable than others.

Mechri, de Peretti, and Hamad (2022) defines the exchange rate impact on stock market dynamics was proposed. The dataset proposed was the Tunis stock exchange from January 2002

to January 2017, with 181 observations per series in this paper. The pre-processing technique was a unit root test to avoid spurious regression with natural logarithm, specification test, Hadri unit root test, and ADF test. The methodology used was Empirical models, the GARCH model, Multi regression model, neural regression, and Breush-Godfrey serial correlation test. The results showed that exchange rate volatility has vast changes in stock market fluctuations. Mashadihasanli (2022a)presented forecasting stock market prices. The dataset used was taken from Istanbul University period January 2009 to March 2021 with 147 total observations (In sample data and data sample). The pre-processing technique used was the unit root test. Feature extraction used was the Ramsey RESET test. The methodology used was the ARIMA model, Serial correlation. It was revealed by the study that the ARIMA model is the best-fit model. Therefore, the results of this paper are similar to many previous papers as well.

Guan, Liu, and Cheng (2022)predict stock market crashes with the use of social media platforms was introduced. The dataset was used from market sentiments after the March 2020 crash using social media information, 2000 firms listed on NASDAQ, and 1619 final firms from 34 sectors. The pre-processing technique used was clustering and normalization. The feature extraction used was the prototype extraction function. The methodology implemented was DTW, CVIs, ADF, KPSS, Granger causality, and the VAR model. The results showed that group 1 value is 0.0702 & group 2 value is -0.0270. group 1 value is -1.4009 & group 2 value is -1.1599. In Group 1, the impact of cumulative Twitter postings was found to be stronger than in Group 2. Saha, Gao, and Gerlach (2022a)preferred a graph-based approach in the stock market. The dataset was used from different graph approaches through social media, historical return data, and stock description documents. The preprocessing was sampling, lagging, window size, and threshold. The feature extraction used was Pearson's correlation coefficient. The methodology used were ARMA, FIEGARCH, LSTM, ARFIMA, SM, ANN, CNN, MAPE, and MSE. Portfolio performance can also be improved by graph-based approaches, as shown by the results.

Lv, Wu, Xu, and Shu (2022a)proposed the stock index prediction. The dataset was used from four major global stock indices (DAX, HSI, S&P 500, and SSE) from 13 December 2007 to 12 December 2020, 10% of the dataset was used for testing. The pre-processing techniques were EMD, EEMD, CEEMDAN, and Gaussian white noise. The feature extraction used was the ADF stationarity test. For time series forecasting based on CEEMDAN the CAL Hybrid ARMA LSTM model and evaluation metrics were used in the proposed stock index prediction. It was found that the results varied with the decomposition of data and the CAL model showed the highest prediction validation. Cai, Song, Wang, and Chang (2014)suggested time series forecasting. The dataset was used from IBM stock daily close price from 1 January 2008 to 31 December 2013. The pre-processing used was a Gaussian function. The feature extraction was done using NMSE, MAE, and DS. The methodology included the usage of SVM and Directed Weighted Chunks SVMs. It was shown that the accuracy of directed weighted chunking SVMs could be improved by checking out suitable parameters for different kernel functions.

Napitupulu, Sambas, Murniati, Kusumaningtyas, and others (2022)The stock market prediction model was initiated using machine learning methods. The dataset was obtained from the stock market pharmaceutical Industry. The data is processed with normalization. The feature extraction is done by the back propagation algorithm. The methodology used was NARX, LSTM, ANN, and evaluation sets. The results showed that ANN-based machine learning approach shows better results. Adenomon, Maijamaa, and John (2022b)came up with covid-19 out-turn on Nigeria's stock exchange performance. The dataset of the Nigeria stock exchange (2 March 2015-16 April 2020). The pre-processing used was min-max normalization. The feature extraction was a unit root test. The methodology used was the GARCH model, QGARCH, and model selection criteria. The results showed that covid-19 hurt the performance of stock returns in the Nigeria stock exchange. Kumbure, Lohrmann, Luukka, and Porras (2022)suggested Machine Learning techniques literature review. The dataset was obtained from 138 journals from the period 2000-2019 and 2173 unique variables. The preprocessing technique used was data cleaning and scaling. The feature extraction technique was feature generation, feature selection data splitting, PCA, and wavelet transfer. The methodology used was ML, SUM, FTS, DNN 15, and LSTM. And the result of this paper had a slight difference from previous studies. LSTM was better than other deep learning models/methods.

Soni, Shirvastava, Motwani, and Pradesh proposed feasibility study of the stock market. The dataset was obtained from Google and Twitter. The pre-processing technique used was text data for sentiment analysis. The feature extraction technique used was a fuzzy logic module. The methodology used was ANN, SUM, LSTM, linear regression, and recurrent, neural network (RNN). The result of this paper was that AI is important for the analysis of the stock market yet there are alternative challenges. Akhtar et al. (2022b)recommended stock market prediction. The dataset was obtained from the Kaggle dataset, 75% training set, and 25% testing set. The pre-processing technique used was Python news analysis and filtering. The feature extraction technique used was text summarization. The methodology used was LSTM, SUM, forest algorithm, and random wooded area algorithm. The result was the accuracy of the SVM model was 78.7% and the random forest model was 80.8%. It showed a clear difference in model accuracy.

Chhajer, Shah, and Kshirsagar (2022)The applications of artificial neural networks were brought forward. The dataset was obtained from S&P500, NASDAQ-100, Gold, and CANUSD, stock data via web scrapings, and different datasets for three different algorithms: social media, news, and twitter. The pre-processing technique used was GASVM, K nearest neighbor bagging. The feature extraction technique used was AdaGrad RMSProp. The methodology used was evaluation metrics, ANN, SVM, and LST. The result showed that these Machine Learning Models were used to show more accurate results for stock market prediction. SVM is 83.72% accuracy, The prediction accuracy of ANN was found to be 63.30%. Huang, Gong, Chen, and Wen (2013)The HAR-CJ-M model was proposed for the Chinese stock market for measuring and forecasting volatility. The dataset was obtained from 300 samples from Shanghai and Shenzhen stock markets, WIND financial database from the time 20 April 2007 to 20 April 2012, 1199 trading days, 58751 data. The preprocessing technique was an ADF test. The feature extraction technique used was Lagged correlation function. The methodologies were the HAR-CJ model, parameter estimation, evaluation matrices, HAR-ARV model. The HAR-CJ model showed more accurate results than the other two.

Karthik (2022) showed the study on forecasting variance of the NiftyIt index. The dataset was taken from the NiftyIT index of the last 10 years from the Bombay stock exchange divided into a 90% training set and 30% testing LSTM and DNN. The data was pre-processed using Backpropagation algorithms and sigmoid function for feature extraction in a way to have clarity in the dataset. The results showed that the DNN and LSTM-RNN models both work efficiently but due to higher accuracy of the model LSTM with 98%. The model of LSTM was better due to the extra memory component for time series data.

Agyei, Bossman, Asiamah, Adela, and others (2022)proposed insights from the time-frequency domain. The dataset was taken from 11 African countries, the stock exchange rate from Yahoo, and the stock market data from Equity-RT. The time period and finance of the dataset were divided into two parts (13 February 2013-6 May 2021 & 31 March 2020 - 6 May 2021). The pre-processing technique used was Scale localization and smoothing. The feature extraction used was maximal overlap discrete wavelet transform and lagging. The methods were P-WC and BW coherence. In conclusion, it was predicted that African economies have a high chance of market integration in the coming years.

Zhu, He, and Wang (2021)The time-frequency effect on high-frequency stock prices was discussed. The International EPU dataset was taken from China's stock market from the time of January 2000 - February 2021 compiled by Bakar et.al. The pre-processing was done using a smoothing technique. The features were extracted using the ADF test, and unit root test. The methods used were the ARCH model, Statistics test, and Robustness test. It was shown by the results that a spillover of 1.34% exists for China's EPU in the long-term frequency.

Alsulmi and Al-Shahrani (2022)initiates stock trading for decision-making based on Machine Learning. Capital market authority historical data released by Saudi (12 years data) January 2010- August 2021,2910 daily trading instances per stock. The pre-processing technique used is labeling, data scaling, and normalization. Feature extraction was conducted by feature generation. The methods used were LSTM,10-fold cross-validation, SVM, RF, ANN. The results showed a comparison of results of Morgan Stanley SA 84%, the model proposed in this paper shows 86%. Therefore, all enhancement potentially increases the framework performance.

Table 2: Metadata for Machine learning

References	Dataset	Pre-processing	Feature Extraction	Methodology	Results
(Zhou et al., 2018)	10 million public stock relevant tweets and 3 million investors on Weibo 1 Dec 2014 to 7 Dec 2015	Filtering Naive Bayes Classifier	Manual selection using keywords (Emotion classification and online emotion)	SVM-ES, SVM-MR K-means Logistic Regression	SVM-ES gives 65.60% and SVM gives 52.83% so SVM-ES is better than other models
(Fataliyev et al., 2021)	Textual data from different social media platforms (Twitter, Reuters,Bloomberg, Blogging, News, Yahoo Finance, and Google Finance)	Bag of words, Word embedding, event embedding, Paragraph vector, aspect-based sentiments, LDA	Event extraction, sentiment extraction, extract sentence level, document level sentiments	Statistical techniques, ANN, machine learning, deep learning, linear regression, auto-regression, GARCH, ARMA, SVR, RF, SVM, RNN, LSTM, RCNN	Hybrid analysis models have shown great potential and can usually lead to better results than conventional methods
(RINGMU & OUMAR, 2022b)	Oil & Gas sector of NYSE (59 industries) Jan 2015 to Dec 2019	Convenient Sampling	Salient Dynamic features	ARIMA, Box Jenkins 1973 method	random walk-based model best fits NYSE stock prices
(A. Amunugama, H. Abeysundara, & U. Dissanayaka, 2022)	Annual Report of Central Bank of Sri Lanka Jan 2015 -Jun 2019 50 trading days Jan 2015- June 2019 Sample of 20 companies	Chi-Square test, Autocorrelation test, Run test	RMSE, MAPE, AIC, Box Jenkins test	ARIMA, ARCH, Heteroskedasticity, FBMAP (For future stock prediction)	FBMAP is more suitable than MAPE
(Mechri, Ben Hamad, de PERETTI, & Charfi, 2018)	Tunis Stock Exchange The Bosra Istanbul 100 Index Dataset Period: Jan 2002- Jan 2017 (181 observation per series)	Natural logarithm, Specification test, Hadri unit test, ADF test	Unit root test to avoid spurious regression	Empirical model, GARCH, Multiple Regression model, Neural regression, Breush-Godfrey serial correlation test, Jarque-Bera normality test	Exchange rate volatility has vast changes on stock market fluctuations
(Mashadihasanli, 2022b)	data provided by Istanbul University total no. of observation:147 In-sample-data:2009 Jan to 2020 Dec Out-Sample-Data:2021 Jan to 2021 March	Unit root test	Ramsey RESET test	ARIMA Model, Serial Correlation, LM test, White Test	The study reveals that the ARIMA model is the best-fit model. The result of this paper is similar to many previous papers as well
(Guan, Liu, & Cheng, 2021)	social media during and after March 2020 crash Final 1619 firms from 34 sectors Twitter data	Clustering & Normalization	Prototype extraction function	DTW, CVIs, ADF Granger Causality VAR model	In Eq 2 group 1 value is 0.0702 & group 2 value is -0.0270 In Eq 3 group 1 value is -1.4009 & the group 2 value is -1.1599 group 1 is stronger
(Saha, Gao, & Gerlach, 2022b)	Different graph-based approaches through social media, stock description documents, and historical return data	Sampling, lagging, window size, threshold	Person correlation coefficient	ARMA models, FEGARCH, MI, CMI, PMI, PMIME, LSTM, MST, PMFG, TMFG, clustering, DBHT, ARMA, ARFIMA, SVM, ANN, CNN, GGGCN, MAPE, MSE	Shows that graph-based approaches can also improve portfolio performance
(Lv, Wu, Xu, & Shu, 2022b)	Four major global stock indices (DAX, HIS, PSSO, and SSE)	EMD, EEMD, CEEMDAN, Goussian white noise	LSTM, ARMA, ADF stationarity test	CAL, hybrid ARMA-LSTM model for time series forecasting based on CEEMDAN, Evaluation Matrices, LSTM ANN model, ARRIMA-ANN	Experimental results vary with decomposition CAL was used and shows the highest prediction validation

				model, Regression analysis	
(Cai et al., 2014)	IBM stock daily close price 01 Jan 2008 to 31 Dec 2013	Gaussian function	NMSE, MAE, DS	The proposed algorithm improves the computational speed with accurate results	Different kernel functions and suitable parameters can be checked out to improve the accuracy of directed weighted chunking SVMs
(Napitupulu, Sambas, Murniati, & Kusumaningtyas, 2022)	Stock market pharmaceutical industry	Normalization	Back progression algorithm	NARX, LSTM, Evaluation sets ANN	machines learning approach shows better results
(Adenomon, Maijamaa, & John, 2022a)	Nigeria Stock exchange period of dataset -2 March 2015-16 April 2020-2 January 2020-16 April 2020	Min-Max normalization	Unit root test	GARCH model, QGARCH model, Model selection criteria	The results show that Covid-19 hurt the performance of stock returns in the Nigeria Stock Exchange
(Kumbure et al., 2022)	138 Journals 2000-2019 2173 unique variables	Data Cleaning Scaling	Feature Generation, feature selection, Data splitting, PCA, and wavelet transform	evaluation matrices, machine learning techniques, SVM	results of this paper have a slight difference from previous studies, LSTM is better than other deep-learning models\methods
(Soni et al.)	Google & Twitter	Text data for sentiment analysis	Fuzzy logic module	ANN, SVM, LSTM, Linear Regression, Recurrent Neural Network (RNN)	AI is important for analysis of stock market yet there are alternatives challenges
(Akhtar et al., 2022a)	Kaggle Dataset,75% training set,25% testing set.	Python news analyzer, Filtering	Text Summarization	LSTM, SVM, forest algorithm-sampling techniques, Random worded area algorithms.	Accuracy of SUM model is 78.7%. Random forest model is 80.8%.it shows clear difference of model accuracy
(Chhajer et al., 2022)	P 500, set 50 (2007-2014), Gold, NASDAQ100 and CNUSD, stock data via webscraping, Different dataset for three different social media, News, t witter	GASUM, K Nearest-Neighbor, Bagging	AdaGrad RMSProp	Evaluation matrices, ANN, SVM, LST	results for stock market prediction, SVM-83.72% accuracy, ANN-63.30% LSTM is proven to be better than others
(Huang et al., 2013)	300 samples from shanghai and shenzhen stock market, WIND financial database 20 April 2007 - 20 April 2012,1199 trading days 58751 data	ADF test	lagged correlation function	Parameter estimation, HARARV model, HAR-CJ model evaluation matrices	The HAR-CJ model shows more accurate results than others. Due to higher accuracy of the LSTM model with 98%.
(Karthik, Rao, & Reddy, 2022)	NiftyIT index past 10 years from Bombay stock exchange ,90 % for training and 30% for testing LSTM and DNN	Back propagation algorithms	Sigmoid function	LSTM, Evaluation Metrics, DNN	DNN was considered for forecasting, LSTM model shows more results due to extra memory component for time series data
[34]	Stock Market data from Equity RT Stock Exchange rate data from Yahoo finance. Exchange rate were measured as USD. Two datasets 13 Feb 2013-6 may 2021(stock exchange rates for 11 African countries)	Scale Local isations Smoothing	Maximal Overlap discrete wavelet transform (MOD WT)	partial wavelet transforms to assess the pandemic's impact Wavelet technique, and P-WC, Skewness, Kurtosis, Jarque-B era, ADF, PP, bivariate wavelet coherence, Lagging	Found positive co-movement led by EXR returns was found Sout Africa, Kenya, Botswana, Nigeria, and Tunisia Yet negative in Zambia

References	Dataset	Pre-processing	Feature Extraction	Methodology	Results
[35]	Baker et al. from January 2000 to February 2021 by China's stock markets	Sampling, Smoothing	continuous wavelet definition	ADF test, ARCH model, Statistics test unit root test, Robustness test	In Long-term frequency, China's EPU, spillover to it is 7.34%
[36]	Historical data released by Saudi Capital authority (last 12 years data) Jan 2010-August 2021 Saudi stock exchange (Tadawul) 2910 daily tradins instances per stock	Labeling, Data Scaling, Normalization	Feature Generation	LSTM 10-fold cross-Validation SVM, RF, ANN	Comparison of results of Morgan Stanley 84%, model proposed in this paper sows 86% All enhancements potentially increase the frameworks performance

2.3. Artificial Neural Network

Yildiz, Yalama, and Coskun (2008)The forecasting of the National Istanbul stock exchange 100 indexes were proposed. The dataset was obtained from the Istanbul stock exchange market and macroeconomic data from the Bank of Turkey. A total of 1805 data points were used for training and 100 for testing. The pre-processing included the total function and transfer function. Feature extraction was MSE, Gradient descent method, Delta Algo. The methodology used was ANN. The results showed an accuracy of 74.5% which ensures that ANN was a good model for stock prediction. Azhar Ali Marri, M. Ghulam, and H. Talpur (2022)introduced evaluation of stochastic. The dataset consisting of 7241 daily observations of the KSE 100 index (daily closing price index) was obtained from finance.yahoo.com for the period of 01-01-1990 to 31-12-2019. The pre-processing technique used was Box Jenkin. The feature extraction technique was the Ljung Box Test. The methodology used was ANN, evaluation, matrices, and ARIMA. The paper found that the ANN model with 84% accuracy outperformed as compared to other models in this paper.

Al-Najjar (2022a)The dataset was obtained from Investing.com and consisted of S&P 500, CAC, Nikkei, DAX, NASDAQ, and HSI from the period of 2008-2019 for evaluating the inclination between emerging and international stock markets using ANN. Sampling was used as a pre-processing technique. Further data was extracted using the R Square and F value test. The methodology included MLP statistics, Linear regression, and ANN. It was shown by the results that (S&P) 500 index correlated 50%, while the others had less than 50%. However, it was also shown that all indices were part of the best model. Manikandan and Subha (2016)gave software-style challenges in time series prediction systems. The dataset was taken from five currencies of Daily foreign exchange rates (US$) from a period of 1993 June- 2015 march by OUNDA.com. The pre-processing was done using the Variance gamma method, NAR, threshold. The feature extraction was performed with NARX. The methodology implemented was ANN, The laven-bag - Marquardt backpropagation algorithm, and evaluation metrics. The results showed that the algorithm proved to be accurate in economic indicators and combining techniques to perform the prediction with higher accuracy of 88.3%.

Table 3: Metadata for Artificial Neural Network

References	Dataset	Pre-processing	Feature Extraction	Methodology	Results
Yildiz et al. (2008)	Istanbul Stock Exchange Market Macroeconomic data from Central Bank of Republic of Turkey 1805 for training & 100 for testing	Total Function Transfer Function	MSE, Gradient Descent, Delta Algo	ANN	74.5% accuracy, which ensures that ANN is a good model for Stock prediction
Azhar Ali M Marri, M Ghulam, and H Talpur (2022)	Secondary data of KSE 100 Index From finance yahoo. com 01-01-1990 to 31-12-2019 7241 observations	Box Jenkins	Jung Box test	ANN, Evaluation metrics, ARIMA	ANN is better than ARIMA model
Al-Najjar (2022b)	S&P 500, NASDAQ, Nikkei, DAX,C AC,HSI	Sampling	Linear regression	MLP, statistics, F value test, ANN	The results showed significant effect, all indices are part of best

1120

	2008 -2019 Investing.com			model NASDAQ:0.617 S&P 500:0.456 DAX -0.425
Manikandan and Subha (2016)	five currencies daily foreign exchange rates (US$) June 1993 to March 2015 by Oanda.com	Variance Method threshold	Gamma NAR, NARX	Evaluation Metrics, ANN, The Lavenberg Marquardt back-propagation algorithm	accuracy found in combining technical and economic indicators for better prediction.

3. Dataset Availability

One of the challenges in the research of stock market area price prediction is to finding datasets. we discuss the available datasets related to different stock exchanges in this section.

Table 4

References	Dataset
T. H. Aldhyani and A. Alzahrani (2022)	Tesla, Inc 4 August 2014 - 17 August 2017 Apple, Inc 3 January 2010 - 28 February 2020 30% of the dataset as a test set and 70% of the dataset as a training Set. https://www.kaggle.com/code/faressayah/stock-market-analysisprediction-using-lstm/data (accessed on 25 August 2022
Albahli et al. (2022b)	Four major global stock indices (DAX, HIS, PSSO, and SSE) Publicly dataset was available analyzed by this study. https://cn.investing.com/indices/germany-30-historical-data. https://cn.investing.com/indices/hang-sen-40-historical-data. https://cn.investing.com/indices/us-spx-500-historical-data. https://cn.investing.com/indices/shanghai-composite-historical-data.
(Yujun et al., 2020a)	Yahoo Finance - Stock Market Live, Quotes, Business & Finance News from (http://finance.yahoo.com).
(Zhu et al., 2021)	Economic Policy Uncertainty Index from https://www.policyuncertainty.

After reviewing the literature related to the prediction of stock exchange price, there is still plenty of areas that requires attention. It is suggested that advanced approaches of deep learning or hybrid models that use both stock price indexes and sentiment news analysis should be implemented to improve the knowledge in stock market price prediction research. Multinational datasets and datasets of less than a day should be used for the analysis of the price. For ease of future researchers, more datasets should be available publicly.

4. Conclusion

A country's economic status has become fundamentally linked to the stock market. The stock market has become a challenging task nowadays by the price of forecasting. Many researchers conducted a study on stock market price prediction but none of them gave the novelty of a price prediction interval of less than one day. In our proposed work, we use the future work of the previously studied paper, which is our novelty: This study aims to predict stock market prices within a day and extend the research to include European and Asian stock markets. The results produced from this project will benefit the business in terms of capturing useful insights into various factors influencing stock exchange strategies.

References

Karthik, C. a. R., B Ashwath and Reddy, NV Subba and others. (2022). *{Forecasting variance of NiftyIT index with RNN and DNN}*, : {Journal of Physics: Conference Series},.

Adenomon, M. O., Maijamaa, B., & John, D. O. (2022a). The effects of COVID-19 outbreak on the Nigerian stock exchange performance: evidence from GARCH models. *Journal of Statistical Modeling & Analytics (JOSMA), 4*(1). doi:https://doi.org/10.22452/josma.vol4no1.3

Adenomon, M. O., Maijamaa, B., & John, D. O. (2022b). The effects of Covid-19 outbreak on the Nigerian Stock Exchange performance: Evidence from GARCH Models. *Journal of Statistical Modeling & Analytics (JOSMA), 4*.

Agyei, S. K., Bossman, A., Asiamah, O., Adela, V., & others. (2022). Exchange rate, COVID-19, and stock returns in Africa: insights from time-frequency domain. *Discrete Dynamics in Nature and Society, 2022*.

Ahmed, D. M., Hassan, M. M., & Mstafa, R. J. (2022). A Review on Deep Sequential Models for Forecasting Time Series Data. *Applied Computational Intelligence and Soft Computing, 2022*. doi:https://doi.org/10.1155/2022/6596397

Akhtar, M. M., Zamani, A. S., Khan, S., Shatat, A. S. A., Dilshad, S., & Samdani, F. (2022a). Stock market prediction based on statistical data using machine learning algorithms. *Journal of King Saud University-Science, 34*(4), 101940. doi:https://doi.org/10.1016/j.jksus.2022.101940

Akhtar, M. M., Zamani, A. S., Khan, S., Shatat, A. S. A., Dilshad, S., & Samdani, F. (2022b). Stock market prediction based on statistical data using machine learning algorithms. *Journal of King Saud University-Science, 34*, 101940.

Al-Najjar, D. (2022a). The Co-Movement between International and Emerging Stock Markets Using ANN and Stepwise Models: Evidence from Selected Indices. *Complexity, 2022*.

Al-Najjar, D. (2022b). The Co-movement between international and emerging stock markets using ANN and stepwise models: evidence from selected indices. *Complexity, 2022*, 1-14. doi:https://doi.org/10.1155/2022/7103553

Alaameri, Z. H. O., & Faihan, M. A. (2022a). Forecasting the Accounting Profits of the Banks Listed in Iraq Stock Exchange Using Artificial Neural Networks. *Webology, 19*, 2669–2682.

Alaameri, Z. H. O., & Faihan, M. A. (2022b). Forecasting the Accounting Profits of the Banks Listed in Iraq Stock Exchange Using Artificial Neural Networks. *Webology, 19*(1), 2669-2682. doi:https://doi.org/10.14704/WEB/V19I1/WEB19177

Albahli, S., Nazir, T., Mehmood, A., Irtaza, A., Alkhalifah, A., & Albattah, W. (2022a). AEI-DNET: a novel densenet model with an autoencoder for the stock market predictions using stock technical indicators. *Electronics, 11*, 611.

Albahli, S., Nazir, T., Mehmood, A., Irtaza, A., Alkhalifah, A., & Albattah, W. (2022b). AEI-DNET: a novel densenet model with an autoencoder for the stock market predictions using stock technical indicators. *Electronics, 11*(4), 611. doi:https://doi.org/10.3390/electronics11040611

Aldhyani, T. H., & Alzahrani, A. (2022). Framework for predicting and modeling stock market prices based on deep learning algorithms. *Electronics, 11*(19), 3149. doi:https://doi.org/10.3390/electronics11193149

Aldhyani, T. H. H., & Alzahrani, A. (2022). Framework for predicting and modeling stock market prices based on deep learning algorithms. *Electronics, 11*, 3149.

Alsulmi, M., & Al-Shahrani, N. (2022). Machine Learning-Based Decision-Making for Stock Trading: Case Study for Automated Trading in Saudi Stock Exchange. *Scientific Programming*.

Amunugama, A., Abeysundara, H., & Dissanayaka, U. (2022). ARIMA and FBMAP approach for forecasting daily stock price in Colombo Stock Exchange, Sri Lanka. *Ceylon Journal of Science, 51*(3), 259-267.

Amunugama, A. W. V. M., Abeysundara, H. T. K., & Dissanayaka, U. N. B. (2022). ARIMA and FBMAP approach for forecasting daily stock price in Colombo Stock Exchange, Sri Lanka. *Ceylon Journal of Science, 51*, 259–267.

Cai, Y., Song, L., Wang, T., & Chang, Q. (2014). Financial time series forecasting using directed-weighted chunking SVMs. *Mathematical Problems in Engineering, 2014*. doi:https://doi.org/10.1155/2014/170424

Chhajer, P., Shah, M., & Kshirsagar, A. (2022). The applications of artificial neural networks, support vector machines, and long–short term memory for stock market prediction. *Decision Analytics Journal, 2*, 100015. doi:https://doi.org/10.1016/j.dajour.2021.100015

Fataliyev, K., Chivukula, A., Prasad, M., & Liu, W. (2021). Stock market analysis with text data: A review. *arXiv preprint arXiv:2106.12985*. doi:https://doi.org/10.48550/arXiv.2106.12985

Fleischer, J., Von Laszewski, G., Theran, C., & Bautista, Y. J. P. (2022). Time series analysis of blockchain-based cryptocurrency price changes. *arXiv preprint arXiv:2202.13874*. doi:https://doi.org/10.48550/arXiv.2202.13874

Guan, C., Liu, W., & Cheng, J. Y.-C. (2021). Using social media to predict the stock market crash and rebound amid the pandemic: the digital 'haves' and 'have-mores'. *Annals of Data Science*, 1-27. doi:https://doi.org/10.1007/s40745-021-00353-w

Guan, C., Liu, W., & Cheng, J. Y.-C. (2022). Using social media to predict the stock market crash and rebound amid the pandemic: the digital 'haves' and 'have-mores'. *Annals of Data Science, 9*, 5–31.

Huang, C., Gong, X., Chen, X., & Wen, F. (2013). *Measuring and forecasting volatility in Chinese stock market using HAR-CJ-M model.* Paper presented at the Abstract and Applied Analysis.

Jung, G., & Choi, S.-Y. (2021a). Forecasting foreign exchange volatility using deep learning autoencoder-LSTM techniques. *Complexity, 2021*, 1-16. doi:https://doi.org/10.1155/2021/6647534

Jung, G., & Choi, S.-Y. (2021b). Forecasting Foreign Exchange Volatility Using Deep Learning Autoencoder-LSTM Techniques. *Complexity, 2021*.

Karthik, C., Rao, B. A., & Reddy, N. S. (2022). *Forecasting variance of NiftyIT index with RNN and DNN.* Paper presented at the Journal of Physics: Conference Series.

Kumbure, M. M., Lohrmann, C., Luukka, P., & Porras, J. (2022). Machine learning techniques and data for stock market forecasting: A literature review. *Expert systems with applications*, 116659. doi:https://doi.org/10.1016/j.eswa.2022.116659

Lv, P., Wu, Q., Xu, J., & Shu, Y. (2022a). Stock Index Prediction Based on Time Series Decomposition and Hybrid Model. *Entropy, 24*, 146.

Lv, P., Wu, Q., Xu, J., & Shu, Y. (2022b). Stock index prediction based on time series decomposition and hybrid model. *Entropy, 24*(2), 146. doi:https://doi.org/10.3390/e24020146

Manikandan, N., & Subha, S. (2016). Software design challenges in time series prediction systems using parallel implementation of artificial neural networks. *The Scientific World Journal, 2016*. doi:https://doi.org/10.1155/2016/6709352

Marri, A. A., Ghulam, M., & Talpur, H. (2022). Evaluation of Stochastic and ANN Model for Karachi Stock Exchange Prices Pre-diction. *Int. Trans. J. Eng. Manag. Appl. Sci. Technol, 13*, 1–11.

Marri, A. A., Ghulam, M., & Talpur, H. (2022). Evaluation of Stochastic and ANN Model for Karachi Stock Exchange Prices Pre-diction. *Int. Trans. J. Eng. Manag. Appl. Sci. Technol, 13*, 1-11. doi:https://doi.org/10.14456/ITJEMAST.2022.23

Mashadihasanli, T. (2022a). Stock Market Price Forecasting Using the Arima Model: an Application to Istanbul, Turkiye. *Journal of Economic Policy Researches, 9*, 439–454.

Mashadihasanli, T. (2022b). Stock Market Price Forecasting Using the Arima Model: an Application to Istanbul, Turkiye. *Journal of Economic Policy Researches, 9*(2), 439-454. doi:https://doi.org/10.26650/JEPR1056771

Mechri, N., Ben Hamad, S., de PERETTI, C., & Charfi, S. (2018). The impact of the exchange rate Volatilities on stock markets dynamics: Evidence from Tunisia and Turkey. *Christian and Charfi, Sahar, The Impact of the Exchange Rate Volatilities on Stock Markets Dynamics: Evidence from Tunisia and Turkey (September 19, 2018)*.

Mechri, N., de Peretti, C., & Hamad, S. B. (2022). The Impact of the Exchange Rate Volatility on Stock Markets Dynamics in Tunisia and Turkey: An Artificial Neural Network Analysis. *Global Economics Science*, 1–21.

Mostafa, M. M. (2010). Forecasting stock exchange movements using neural networks: empirical evidence from Kuwait. *Expert systems with applications, 37*(9), 6302-6309. doi:https://doi.org/10.1016/j.eswa.2010.02.091

Mostafa, M. M. (2010). Forecasting stock exchange movements using neural networks: empirical evidence from Kuwait. *Expert systems with applications, 37*, 6302–6309.

Mustafa, S., Bajwa, A. A., & Iqbal, S. (2022a). A new fuzzy grach model to forecast stock market technical analysis. *Operational Research in Engineering Sciences: Theory and Applications, 5*, 185–204.

Mustafa, S., Bajwa, A. A., & Iqbal, S. (2022b). A new fuzzy grach model to forecast stock market technical analysis. *Operational Research in Engineering Sciences: Theory and Applications, 5*(1), 185-204. doi:https://doi.org/10.31181/oresta190101s

Napitupulu, H., Sambas, A., Murniati, A., & Kusumaningtyas, V. A. (2022). Artificial Neural Network-Based Machine Learning Approach to Stock Market Prediction Model on the Indonesia Stock Exchange During the COVID-19. *Engineering Letters, 30*(3).

Napitupulu, H., Sambas, A., Murniati, A., Kusumaningtyas, V. A., & others. (2022). Artificial Neural Network-Based Machine Learning Approach to Stock Market Prediction Model on the Indonesia Stock Exchange During the COVID-19. *Engineering Letters, 30*.

RINGMU, H. S., & OUMAR, S. B. (2022a). Forecasting stock prices in the New York stock exchange. *Journal of Economics Bibliography, 9*, 1–20.

RINGMU, H. S., & OUMAR, S. B. (2022b). Forecasting stock prices in the New York stock exchange. *Journal of Economics Bibliography, 9*(1), 1-20.

Saha, S., Gao, J., & Gerlach, R. (2022a). A survey of the application of graph-based approaches in stock market analysis and prediction. *International Journal of Data Science and Analytics*, 1–15.

Saha, S., Gao, J., & Gerlach, R. (2022b). A survey of the application of graph-based approaches in stock market analysis and prediction. *International Journal of Data Science and Analytics, 14*(1), 1-15. doi:https://doi.org/10.1007/s41060-021-00306-9

Soni, S., Shirvastava, A. K., Motwani, D., & Pradesh, G. Feasibility Study of Stock Market Prediction for Sentiment Analysis using Artificial Intelligence.

Suphawan, K., Kardkasem, R., & Chaisee, K. (2022a). A Gaussian Process Regression Model for Forecasting Stock Exchange of Thailand. *Trends in Sciences, 19*(6), 3045-3045. doi:https://doi.org/10.48048/tis.2022.3045

Suphawan, K., Kardkasem, R., & Chaisee, K. (2022b). A Gaussian Process Regression Model for Forecasting Stock Exchange of Thailand. *Trends in Sciences, 19*, 3045–3045.

Teng, X., Wang, T., Zhang, X., Lan, L., & Luo, Z. (2020). Enhancing stock price trend prediction via a time-sensitive data augmentation method. *Complexity, 2020*, 1-8. doi:https://doi.org/10.1155/2020/6737951

Wang, J., Wang, J., Fang, W., & Niu, H. (2016). Financial time series prediction using elman recurrent random neural networks. *Computational intelligence and neuroscience, 2016*. doi:https://doi.org/10.1155/2016/4742515

Wu, S., Liu, Y., Zou, Z., & Weng, T.-H. (2022a). S_{I}{_{L}{S}{T}}{M}: stock price prediction based on multiple data sources and sentiment analysis. *Connection Science, 34*, 44–62.

Wu, S., Liu, Y., Zou, Z., & Weng, T.-H. (2022b). S_I_LSTM: stock price prediction based on multiple data sources and sentiment analysis. *Connection Science, 34*(1), 44-62. doi:https://doi.org/10.1080/09540091.2021.1940101

Xiao, D., & Su, J. (2022). Research on Stock Price Time Series Prediction Based on Deep Learning and Autoregressive Integrated Moving Average. *Scientific Programming, 2022*. doi:https://doi.org/10.1155/2022/4758698

Yildiz, B., Yalama, A., & Coskun, M. (2008). Forecasting the Istanbul stock exchange national 100 index using an artificial neural network. *An International Journal of Science, Engineering and Technology, 46*, 36-39.

Yujun, Y., Yimei, Y., & Jianhua, X. (2020a). A hybrid prediction method for stock price using LSTM and ensemble EMD. *Complexity, 2020*.

Yujun, Y., Yimei, Y., & Jianhua, X. (2020b). A hybrid prediction method for stock price using LSTM and ensemble EMD. *Complexity, 2020*, 1-16.

Zahra, S. R., Chishti, M. A., Baba, A. I., & Wu, F. (2022a). Detecting Covid-19 chaos driven phishing/malicious URL attacks by a fuzzy logic and data mining based intelligence system. *Egyptian Informatics Journal, 23*, 197–214.

Zahra, S. R., Chishti, M. A., Baba, A. I., & Wu, F. (2022b). Detecting Covid-19 chaos driven phishing/malicious URL attacks by a fuzzy logic and data mining based intelligence system. *Egyptian Informatics Journal, 23*(2), 197-214. doi:https://doi.org/10.1016/j.eij.2021.12.003

Zhou, Z., Xu, K., & Zhao, J. (2018). Tales of emotion and stock in China: volatility, causality and prediction. *World Wide Web, 21*, 1093-1116. doi:https://doi.org/10.1007/s11280-017-0495-4

Zhu, S., He, Z., & Wang, S. (2021). Research on the Time-Frequency Spillover Effect of High-Frequency Stock Price and Economic Policy Uncertainty. *Discrete Dynamics in Nature and Society, 2021*.