



Advancements in Stock Market Prediction Techniques: A Comprehensive Survey

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التنبؤ وتحليل سوق الاوراق المالية باستخدام تقنيات التعلم العميق

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Accepted:

6 /7/ 2024

Published:

30 /9 /2024

ABSTRACT

The stock market, known for its unpredictable nature and complex workings, has been the focus of significant study. Conventional models frequently fail to fully capture the complex and diverse nature of stock market behavior. With the increasing complexity of financial markets, there is a rising demand for advanced strategies that can offer investors precise predictions and essential insight. There are several studies in this regard, from which we chose 24 modern studies from the year 2018 to the year 2023 in various ways to come out with results that are the focus of a new start in the prediction. This review collected different machine learning methods and deep learning techniques, including deep neural networks, which were then used to build powerful prediction models. Integrating behavioral finance theory with quantitative indicators and financial news provides a unique perspective on stock market dynamics. Also, The Efficient Market Hypothesis (EMH) highlights the significant impact of future information, such as news, on the valuation of stocks. Combining deep learning techniques in forecasting and examining the stock market represents an essential stage in financial research, it offers a more intricate comprehension of the intricacies of stock market dynamics. However, obstacles still need to be overcome, and it is essential to use prudence when applying reported accuracies to actual trading situations. The convergence of behavioral finance, efficient market hypothesis, and deep learning present opportunities for more investigation, offering a more comprehensive method of forecasting stock market trends.

Key words: Stock Market Prediction; Deep Learning; Sentiment Analysis; Financial Markets; Trading Strategies.



INTRODUCTION

The financial sector is crucial for the sustained development of the national economy. Due to the rapid advancement of socioeconomic status and the growing openness of the finance sector, investors are now presented with an increasing number of opportunities [1]. Investors who participate in public, private, and mixed-ownership stock exchanges can buy or sell various assets on the stock market [2].

Due to the growing impact of the stock market on economic patterns, predicting the trajectory of stocks has become a prominent subject of study. Several academics have thoroughly researched the stock market to develop ideas for its functioning. Nevertheless, The outcomes of the conducted analysis state that there is no observable relationship between the changes in the stock market [3]. Classical models which have been in use for some time now and which involve the simple analysis, the technical analysis and the statistical methods of analysis are sometimes less effective in providing a comprehensive understanding of the problem. Stock market is an important marker in any economy, the objectives of investing in the stock market are therefore to get an acceptable rate of return and avoid making a loss [4]. Perhaps, an appropriate mathematical model that can be used to predict stock prices could minimize investment risk and improve the effectiveness of the investors' decision-making process. Linear models and ordinary least squares regression are the fundamental tools of traditional statistical and econometric approaches, which are not very useful for analyzing financial data when nonlinear relationships exist. All these methods have shortcomings in terms of capturing and analyzing the nonlinear models in the sphere of finance . Several works demonstrate the emergence of nonlinearities in the financial markets, which is why statistical models are not very effective when it comes to addressing them [5]. New advancements in AI and ML have impacted the financial industry especially in quantitative stock prediction. [6].

Econometrics is the primary method used for traditional stock price prediction. However, numerous additional factors can influence the stock price. Hence, these conventional mathematical models face challenges in incorporating all these aspects comprehensively to generate precise forecasts. Long-standing machine learning approaches, including autoregressive integrated moving averages (ARIMA), are less effective than conventional machine learning models [5]. This model is limited to extracting linear characteristics from the data. Assessing the worth of stocks and predicting their future performance is difficult due to the inherent unpredictability of long-term stock values [7].

The support vector machine (SVM) applications in time series analysis are called support vector regression (SVR). However, SVR continues to face challenges in extracting shallow features [8,9]. NNs are one of the most powerful classes of machine learning algorithms and they also have unique features which give them advantages over classical statistical methods. They are quantitative, data-oriented, and often unpredictable. Through this, the NNs can deal with the so called inaccurate and noisy data, giving them a significant preference for such



situations. Besides, NNs are commonly used in forecasting time series given its high ability to capture complex patterns and interdependencies hidden in data sets [9]. A deep neural network has more layers and a more intricate structure. It can convert basic information into data and more conceptual, high-level information. Furthermore, studies indicate that deep learning models, such as (LSTM)[10], exhibit superior performance compared to machine learning models, such as support vector regression (SVR) [11]. The conventional neural network (CNN) is widely used for tasks such as image recognition, text recognition, target recognition, and target detection [12]. It can analyze characteristics to forecast future market trends. The efficient market hypothesis, introduced by (Eugene Fama), is widely regarded as the most authoritative theory in current financial circles for studying stock market dynamics. Modifications according to this hypothesis, the stock price is mostly influenced by future information, specifically news, rather than being determined by present or historical prices [13].

Recently, several studies have combined financial news with quantitative indicators, drawing on behavioral finance theory, to improve the accuracy of stock prediction [12,14]. Economic news is a crucial information source for investors, influencing their moods and investment behaviors and directly affecting stock prices [15]. Machine learning and deep learning advancements have opened up new possibilities for constructing stock price prediction models using time-series data that exhibit high cardinality, such as large object (LOB) data. These models are used to predict future fluctuations in stock prices [16,17]. Consequently, academics have increasingly focused on this specific topic in recent years. For example, the creators of several modern machine learning and deep learning models can be seen in [13]. These models have been asserted to possess an accuracy exceeding 80%. From an economic viewpoint, these outcomes appear too good to be reliably replicated in real-world stock trading.

RELATED WORK

Introduced a system using long- and short-term memory and a convolutional neural network for predicting stock market movements. The GAN-FD technique enhanced accuracy and minimized forecast error, surpassing standard methods in terms of RMSRE and DPA [6]. Aimed to build a deep long-short-term memory (LSTM) model by utilizing correlated stock technical indicators (STIs) to enhance the accuracy of stock market trend forecasting. The fusion of technical analysis yielded superior outcomes compared to models built with benchmark ML algorithms [17]. Suggested hybrid models involving historical stock prices correlations along with financial news mentions. Predictive performance of the graph convolutional network (GCN) was high in all measurements, thus highlighting the necessity to use both numerical and textual data for effective predictions[18]. Used artificial neural networks (ANNs) to forecast stock prices and achieve a high accuracy rate of 94%. The simplicity and efficiency of ANNs make them an attractive option for stock market prediction [19]. Utilized multi-channel convolutional neural networks (CNNs) to forecast changes in the stock market and enhance the network structure through genetic algorithms (GA). The GA-CNN model outperformed regular artificial neural networks (ANNs) and CNN models, indicating the effectiveness of incorporating genetic evolution into the learning process [20]. Studied the efficacy of LSTM and GRU models in



predicting stock market trends and assessed the importance of integrating financial news emotions. The LSTM-News and GRU-News models, which incorporated financial news feelings, showed enhanced predictive accuracy for stock prices compared to only utilizing stock attributes[21]. Utilized RNNs and LSTM in their study to predict future stock market returns. They used an Indian (SBIN) dataset and got good accuracy levels with up to 97 % for the predicted values based on historical data and 67 % for the trend prediction using the news headlines[22]. Introduced an innovative neural network methodology that utilized deep long short-term memory (LSTM) models for forecasting stock market patterns. The deep LSTM model with embedded layers showcased better performance, achieving high accuracy rates for different indices[23]. Focused on forecasting future values of stock market sectors using diverse machine learning algorithms. The LSTM model achieved a low MAPE value but had a relatively high runtime, highlighting a trade-off between accuracy and computational efficiency[3] . Introduced an advanced model for predicting short-term stock market price trends. This model utilized feature engineering and normalization techniques, with the addition of randomized principal component analysis. The incorporation of these techniques resulted in high levels of accuracy, precision, and recall in the predictions[22]. Presented a stock index prediction model incorporating time series analysis and deep learning techniques. The use of convolutional neural networks (CNNs) for extracting emotional data contributed to the model's predictive capability. The study achieved high accuracy, with a mean absolute percentage error of less than 2% [3]. utilized various models, including long short-term memory (LSTM), XGBoost, linear regression, moving average, and the last value model, for stock price prediction. The LSTM model demonstrated superior performance compared to the other methods, highlighting its ability to capture temporal dependencies and nonlinear patterns in stock prices [25]. came up with a new stock market forecasting model using a hybrid of phase space reconstruction (PSR) and generative adversarial networks (GAN). It was observed that the GAN model performed better than LSTM in predicting market direction and resulting to less processing time and RMSE [26]. Utilized LSTM and a hybrid convolutional neural network (CNN-LSTM) to forecast stock market prices. The CNN-LSTM model exhibited superior performance with higher R-squared values for both Tesla and Apple, indicating its effectiveness in capturing complex patterns [27]. Employed a deep autoencoder and a backpropagation neural network to encode stock price data with many dimensions. While achieving high predictive precision, the model had a 6.94% margin of error, indicating room for improvement [28]. Investigated the effectiveness of AI models, specifically multilayer perceptron (MLP) and long short-term memory (LSTM), in predicting fluctuations in the Saudi Stock Exchange. The results demonstrated a significant level of concurrence between the anticipated values and the real values, thus confirming the effectiveness of the chosen models [29] . Utilized dual long-memory models to examine stock market dynamics in Gulf Cooperation Council countries. The forecasting accuracy reached an impressive 95%, demonstrating the effectiveness of their chosen models[11]. Presented a deep-learning architecture that utilized financial news items to predict stock market movements. The proposed approach achieved an average prediction accuracy of 92.5%, showcasing the importance of incorporating textual data in stock market prediction models[12]. Conducted a



comprehensive analysis of stock portfolios in China's financial market. They employed advanced deep learning neural network (DL NN) models. The proposed DL NN outperformed other indexes regarding various metrics, showcasing promising results for portfolio generation [7]. Focused on predicting volatility in the Asian stock market, achieving a 52% predictive accuracy. The model employed statistical theory, linear support vector machines, and generalizable constraints, providing insights into market conditions [4]. Proposed a two-step system combining mean-variance portfolio selection with machine learning. The study focused on forecasting future stock price fluctuations and outperformed traditional approaches. The methodology involved portfolio optimization and machine learning algorithms, showcasing positive classification reports and high accuracy across multiple stock exchanges [1]. set an objective to develop an AI platform for trend forecasting of stock market using advanced machine learning models. A further addition to the study was the inclusion of the Holt-Winters algorithm, RNN, and RS which were used together with the research. In many cases, the average RMSE was below 50 which is an indication that the method they adopted was effective[2]. Proposed a hybrid model integrating (PCA) and (BP) neural networks for forecasting the closing price of China Merchants Bank. The Bayesian regularization approach outperformed other training procedures, achieving a remarkably low mean absolute percentage error [5]. Aimed to democratize machine learning in influencer marketing, utilizing Autogluon. The Weighted Ensemble_L4 model performed the best, indicating the potential of Autogluon in enhancing influencer marketing strategies[30]. Presented a model for predicting product evaluations using a multi-level deep feature fusion technique on internet reviews. The model outperformed others in various assessment indicators, showcasing its effectiveness in predicting user preferences[13].

Table 1. List of stock markets surveyed

Ref. No.	Dataset	Technique	Result
[1]	The 20 health sector indices sourced from four distinct geographical regions, specifically London, Germany, France, and America.	Portfolio + ML	accuracy 98%
[2]	The study discusses the utilization of a dataset sourced from a global stock market. The collection comprises around fifteen organizations from diverse areas.	Holt-Winters, RNN, RS	RMSE < 50 (Many Cases)
[3]	Tehran stock exchange.	GAN, LSTM, CNN	LSTM model achieved MAPE(0.60,1.18,1.52,0.54), problem runtime(80.902ms per sample)
[4]	Asian stock volatility	Statistical Theory + SVM	52% Predictive Accuracy
[5]	China Merchants Bank (600036)	PCA + BP Neural Networks	Low MAPE 0.0130
[6]	High-frequency data as the dataset.	GAN-FD	RMSRE 65.08% .
[7]	The 111 stable stocks that were chosen	(DL NN)	The model yielded an



	from the component stocks of the China Security Index (CSI) 300.		annualized return of 47.44%
[12]	The dataset including 207,902 financial news articles collected from the Reuter's website.	(DCWR) ,(ICA) ,(HANet)	accuracy of 92.5%.
[11]	Gulf Cooperation Council	ARFIMA Models	The ARFIMA-G-GARCH model exhibits good accuracy reaches 95%.
[13]	The data used in this paper includes essential details and customer reviews for various displays featured on an e-commerce platform	DSCNN, CBAM, BiLSTM	MSE, MAE, RMSE, MAPE, and SMAPE is (0.0269 , 0.0010 , 0.0316 %2.9543 , %2.9597) respectively
[17]	National Stock Exchange (NSE) of India	(LSTM) model is utilised to predict stock prices by including associated Stock Technical Indicators (STIs).	59.25% Prediction Accuracy
[18]	The top 30 corporations listed in the Fortune 500 https://finance.yahoo.com . a collection of 1 million financial news stories https://api.tiingo.com .	GCN based on News Graph (Causation)	RMA5 11.245, MAP 5.113% , MAE 6.824
[19]	Tesla data set	ANN network model	An accuracy rate of 94%
[20]	KOSPI stock index	GA-CNN	Accuracy 73.74%
[21]	The agriculture development bank (ADBL)'s	LSTM and GRU models	LSTM-News: R2 = 0.979
[22]	data set of SBIN stock	RNN , LSTM	accuracy 97%
[22]	The dataset includes 3558 Chinese equities	(LSTM) , (PCA), and (RFE)	The accuracy is 0.93, precision is 0.96 and recall 0.96
[23]	Shanghai A-shares composite index and individual stocks.	(LSTM)	57.2% Accuracy for A-shares
[25]	Dhaka Stock Exchange (DSE)	LSTM	MAPE 0.635.
[26]	Yahoo finance (finance.yahoo.com).	GAN, PSR, LSTM, CNN	GAN Outperformed LSTM
[27]	Tesla, Inc. and Apple, Inc	CNN-LSTM	CNN-LSTM Superior Performance, with R2 for both Tesla (98.37%) and Apple (99.48%) stocks.
[28]	Kweichow Moutai (600519).	DAE-BP	MSE , MRE and MAE (0.043 , 0.0025 , 6.94%) respectively
[29]	Saudi Stock Exchange (Tadawul)	(MLP) , (LSTM)	R2 > 0.9950
[30]	data used in the experiments is obtained from the company and includes tables such as influencers, interactions, and products	Autoglun	The value of R2 has grown to 0.8909, while the mean absolute error (MAE) has decreased to -252.77.



DATASET

In the available literature, various types of datasets are discussed in the context of stock market forecasting. Based on selected studies, it is evident that publicly available datasets are utilized by researchers for this purpose. The majority of these studies focus on predicting the stock market using public data. These datasets are employed for classification or predictive analysis. The models presented in the reviewed articles incorporate different input variables, which play a crucial role in the forecasting process. (Table 2) describes the different types of datasets utilized in chosen studies. In these studies, it has been employed specific techniques in the selection process to identify the most significant input variables for accurate forecasting. This selection is based on evaluating the impact of each input variable on the obtained results, ensuring that only the most influential variables are included in the forecasting models. Most of the literature utilizes daily data for their analysis. When forecasting stock returns or stock indices, existing literature assumes that publicly available information from the past can predict future returns or indices. This information encompasses economic variables [25]. Some studies focus on specific indices, such as the CSI 300 Index [7]. "Standard and Poor's 500 (S & P 500), the Dow Jones Industrial Average (DJIA), the New York Stock Exchange (NSE)", and Other studies, like [2, 17], Integrate the daily closing values of American stock market indices and economic indicators into their models. [7] used 750 rows of historical data for each security to predict the closing price. [26] obtained their dataset from Yahoo Finance, which is an open-source and freely available CSV file. [27] predicted the closing prices of Tesla, Inc. and Apple. Stock market data is a commonly used input variable [4]. Data from the majority of literature includes daily opening/closing prices, daily minimum/maximum prices [2], transaction volume [31], and the closing price of previous days (to a week or month) [3]. The literature frequently integrates stock market data with technical variables, economic variables, or financial indicators based on the specific selection criteria employed by researchers. This combination of different types of data enhances the accuracy and effectiveness of the predictive models used in stock market analysis. Additionally, textual data, particularly financial news, is incorporated alongside stock market data to enhance predictions. The websites from which the articles were downloaded include e-commerce website, Bloomberg, Hadoop, Reuters. For example, [13] collected daily financial news from multiple displays on an e-commerce website, resulting in a total of "42,110" samples. [30] utilized data from the social media and financial news sources to forecast stock market trends for ten consecutive days. "Similarly, Khan et al. (2020b)" found that sentiment and situation features improved prediction accuracy by 0-3% and about 20%, respectively. [30, 31] employed news about finance as Initial data for their machine learning and deep learning models, achieving accuracy rates exceeding 80% and validating the success of their approach.

**Table 2. Dataset used by selected studies.**

Ref. No.	Input variables	Period	No. of instance	Stock market	Stock	Dataset source
[1]	Daily stock price	1987-11-05 to 2021-11-24	-	Stock of USA, London, Germany, France	10stock	different geographic stocks
[2]	Daily stock price	2017-01-01 to 2021-03-31	750	Indian	50 stock	NSE
[3]	technical indicators	2009-11-01 to 2019-11-30		Tehran	4stocks	Co (TSETMC)
[3]	Daily stock price	2015-01-01 to 2019-12-31.	1,219	Shanghai	code 000001, code 399001	Tushar financial
[4]	Daily stock price	7-day randomly selected	-	Asian	100 stock	Asian stock
[5]	technical indicators	from 2015 to 2021		China	600036	iFinD financial
[6]	Daily stock price	2016-01-01 to 2016-12-31	59048 time points	China	CSI 300/40stock	Wind Financial Terminal
[7]	Daily stock price	2018-01-01 to 2021-12-31	-	China	CSI 300\111	CSI 300 index
[12]	Daily stock price	2006-10-01 to 2018-11-01	4160 instances	Standard and Poor's 500 index	500 index	Reuter's website
[11]	Daily stock price	2005-06-01 to 2019-07-01	-	GCC	6 stock	Morgan Stanley Capital International
[13]		-	2560 pieces	online comments		e-commerce website
[17]	Daily stock price	2008-12-17 to 2018-11-15	-	India	3 banks	NSE
[18]	-Daily closing prices. -Minute level data of stock prices	2017-05-01 to 2019-04-01	390 data points 17,204 data points	-	30 stocks 390 minutes daily	https://finance.yahoo.com . https://api.tiingo.com .



[19]	Daily stock price	2010-06-29 2010-07-21	-	Tesla	-	Google finance
[20]	Daily stock price	2000-01-4, to 2016-12-31,		KOSPI	4203 trading days	Bloomberg
[21]	Daily stock price	1996 (days) 42,110 (news)	42,110 samples	Nepal	NEPSE , IPO, ADBL	website (www.sharesansar.com)
[22]	Daily stock price	2009-01-02 to 2019-07-09.		India	Bank of India (stock , news)	SBIN
[22]	Daily stock price	2year	daily fundemental data	china	CSI 300/ 3558 stocks	API
[23]	Daily stock price	2006 -01-01to 2016-10-01	-	Shanghai	TMSE) (600751) and TBEA (600089	Stock Crawler
[25]	Daily stock price	2019-01-01 to 2019-12-31.	236 data points	DSE	-	Dhaka Stock Exchange
[26]	Daily stock price	2013-01-01 to 2018-12-31.	-	various companies	5 sample stock index	finance.yahoo.com
[27]	Daily stock price	2014 -08-04 to 2017-08-17	-	American	AAPL	Tesla, Inc , Apple , Inc
[28]	technical indicators	1156 trading days	-	Different stock indicators	900 pieces	Kweichow Moutai (600519)
[29]	Daily stock price	2018-01-01 to 2020-12-31		Saudi	9sector	https://www.saudiexchange.sa/wps/portal/tadawul/home/
[30]	weekly	-	-	companies in the industry	Instagram	Hadoop

TYPES OF STOCK ANALYSIS

Given many factors, people use different methods to analyze stock price movements.

There are two main types of stock analysis: Fundamental Analysis and Technical Analysis.

- Fundamental Analysis calculates a company's value based on its assets and product value. Factors such as stock trading ratios, market size, demand, management, and economic climate are considered in this approach. Long-term investors typically use Fundamental Analysis.



- Technical Analysis uses charts and mathematical formulas to identify trends and predict stock price movements. It focuses on the price alone without considering the underlying fundamentals. This approach is popular among hedge funds and investment companies.

A combination of fundamental and technical analysis can be utilized to enhance the prediction of stock prices [32].

Techniques used in forecasting stock markets

Given the exponential growth of data, discerning significant patterns within datasets has become exceedingly challenging for human programmers and specialists. Due to this rationale, Artificial intelligence (AI) is used to process complex input data for learning and training. AI techniques like artificial neural networks (ANNs) are used to solve complex problems; ANN and hybrid networks are used to forecast stock market trends. ANNs consist of interconnected "neurons" that process input data for pattern recognition, prediction, and analysis in finance. Different types of neural networks, like ANN, MLP, and RNNs, are used [2,16,21,25], and hybrid models are employed, such as DLNN [8], CNN- LSTM [17], GA-CNN [20]. Recurrent neural networks (RNNs) are also commonly used for sequential pattern learning [2]. Deep learning networks, such as CNNs, LSTMs, and RNNs [3,8,13,16,17,20,22,23,27], have gained popularity due to their ability to handle large and complex datasets. They offer higher prediction accuracy compared to traditional shallow networks. Researchers are shifting towards deep learning networks for better accuracy in prediction (Chopra and Sharma 2021) [33].

THE CHALLENGES ASSOCIATED WITH STOCK MARKET

- 1. Non-Linearity and Complex Patterns: It is suggested that deep learning models can be used to improve the ability to detect complex patterns in data since the standard methods may not be able to identify non-linear relationships.
- 2. Temporal Dependencies: The information related to the stock market contains temporal correlations, meaning the current values rely on previous ones. It is also noted that in some traditional models, it may be difficult to work with long-term dependencies. In the case of temporal dependencies, the attention mechanism and long short-term memory networks (LSTMs) are expected to perform well.
- 3. Feature Learning and Representation: It is believed that deep learning models can 'learn' important features from the raw financial data thus minimizing the need for feature extraction and perhaps, discover hidden patterns that are hard to detect using conventional methods.



- 4. Adaptability to Market Dynamics: Financial markets are ever-changing and shifting trends and sentiments are always in existence. The thesis is therefore designed to study the ability of deep learning models to handle shifts in market environments.

MATERIALS AND METHODS

- **SVM Or SVMs**, also known as Support Vector Machines, are supervised machine learning algorithms that excel in data point classification within an N-dimensional space. They achieve this classification by determining an optimal hyperplane. Although multiple hyperplanes can classify the provided data points, SVM identifies the hyperplane that maximizes the distance between the data points in the n-dimensional space. This ability makes SVMs valuable for regression analysis, as they offer a robust and effective approach to data classification [34]. SVM showed accuracy in predicting stock values across several scenarios. The primary approach is constructing a regression model using the dataset. The predictions may vary in different scenarios. However, their performance could be better when dealing with noisy and unlabeled data [34].

The (SVM) algorithm can be subdivided into the following groups:-

1. Linear SVM is a statistical method that may classify data into two groups using a single straight line when the data is linearly separable. Linear data is divided using a linear (SVM) classifier.
 2. Non-linear SVM is used for data that is not linearly separable, meaning it cannot be separated into groups using a single line. The classification is performed using a non-linear (SVM) classifier, which is determined by the kernel selected during the training of the SVM model [35]
- **LSTM**, Also known as Long Short-Term Memory architecture, it is a specific type of recurrent neural network (RNN) that is widely employed in deep learning applications. LSTMs have feedback connections [36]. LSTM can understand the significance of order dependence in challenges related to sequence prediction. LSTM is capable of retaining historical data. This feature proves beneficial in the context of stock price forecasting, as previous prices have a major impact on predicting future stock prices [37]. A typical LSTM unit comprises four components, a cell, an input gate, an output gate, and a forget gate. The cell functions as a storage unit for retaining values over time, while the gates control the flow of data into and out of the cell. The input gate regulates the influx of new information received as input data, whereas the forget gate manages the storage of information within the cell. The output gate governs the extent to which the cell utilizes the input data and calculates the algorithm's output activation [27].

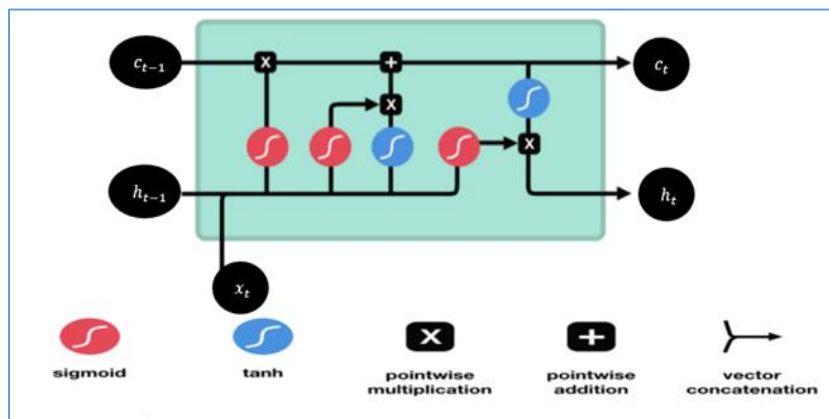


Figure (2.10): The internal architecture of a LSTM[38]

- **BP**, Also Known as Backpropagation Neural Network, is an algorithm that utilizes delta learning rules and the gradient descent method to propagate and correct errors during training. This algorithm sequentially updates the weights and biases of each layer until a convergence condition is met, indicating the end of the training process. The BP neural network incorporates a nonlinear activation function, making it well-suited for nonlinear fitting. Given the complex, nonlinear, and dynamic nature of the stock market, with prices influenced by multiple factors and exhibiting significant volatility, neural network models are highly suitable for analyzing and predicting stock values. Specifically, a BP neural network is employed to construct a regression model for accurate stock value predictions. The algorithm is structured into three layers: the input layer, the hidden layer, and the output layer [28].
- **Autoencoders (AE)** are a unique class of neural networks that stand out from other models due to their unsupervised learning nature, eliminating the need for labeled data during training. AE architecture comprises an input layer, a hidden layer (often denoted as h), and an output layer. The primary objective of autoencoders is to minimize the discrepancy between the input and output, which is represented by the function " $h_{(W,b)}(x) \approx x$," achieved through iterative training [36]. The additional layer introduced post-training is commonly referred to as an encoder, which produces the encoded representation of the input data. The final layer is referred to as the decoder, responsible for decoding the encoded data. However, it typically disregards the output generated by the decoder. Autoencoders may effectively accomplish the task of extracting features and reducing feature dimensionality. Dimensionality reduction can be performed for any dimension by specifying the number of nodes in the hidden layer. Simultaneously, the encoder's output also conveys the more advanced characteristics of the incoming data. The operational mechanism of an AE can be articulated as follows:

$$\text{“ Encoder: } h = f(Wx + b) \quad (1)$$

$$\text{Decoder: } \hat{x} = f \quad (2)$$

Among them, x is the input data, f is the activation function, W and b are the weights and bias values and \hat{x} is the output of the decoder “ [28].

- **The Random Forest Algorithm** It is a supervised machine learning algorithm predominantly employed for classification tasks, although it can also be utilized for regression problems. It utilizes sample data to create multiple decision trees, with each tree constructed using unique sample values. The collective agreement among these decision trees is considered as the ultimate decision. Random Forest aims to address the problem of overfitting but requires substantial computational resources. Notably, the random forest algorithm has exhibited remarkable accuracy when applied to sizable datasets, rendering it well-suited for the analysis of stock market data [39].
- **GRU**, which stands for Gated Recurrent Unit, is networks that are a type of recurrent neural network (RNN) that addresses the issue of gradient vanishing in RNNs using a gating mechanism. This method simplifies the construction of the network while still preserving the effectiveness of long-short-term memory (LSTM) networks [37]. The GRU model comprises an update gate, a reset gate, and a current memory. The output is kept in the final memory. Equations in the context of GRU regulate the transmission of information inside the network. GRU is applied in diverse domains, including natural language processing, machine translation, and text production [21].

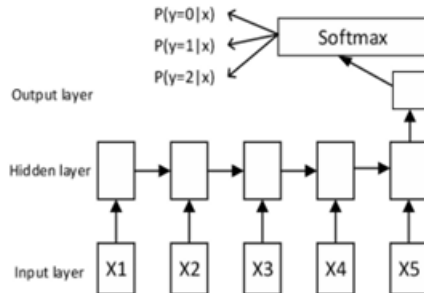


Fig.1. Structure of GRU-based model [37]

- **The Random Walk Hypothesis** claims that stock prices undergo random fluctuations and asserts that previous price changes do not influence current movements. Unlike EMH, this approach specifically emphasizes the analysis of short-term stock market patterns. According to the assumptions proposed by Horne, J. C. et al. and Fama, E. F. from 1967 to 1970, the stock market is expected to exhibit random fluctuations, and it is impossible to predict these fluctuations with an accuracy greater than 50% [40].
- **KNN**, also known as K-Nearest Neighbors, is a simple classification technique that calculates the distance between a new sample and its neighboring samples in the training dataset. The value of K influences the number of closest neighbors used in the classification decision. The new data is divided according to the largest class among its closest neighbors. The approach is



simple, readily executable, and appropriate for small datasets with distinct spatial correlations [36]. This technique is highly effective for constructing and optimizing a stock portfolio. Furthermore, it can also prove beneficial in sentiment analysis [39].

- **Neural Networks** comprise many interconnected units known as neurons, which operate simultaneously to solve a problem. Warren McCulloch and Walter Pitts initially developed them in 1943, basing their approach mainly on the neuronal structure of the human brain. This concept is still only partially followed in modern neural networks. Throughout time, neural networks have seen variations in popularity, primarily due to insufficient technological capabilities to process intricate data.. However, neural networks have garnered substantial attention in recent years. Numerous neural network applications have been developed for these categories [39]. Neural networks are commonly employed in business applications for several reasons. Firstly, they are adept at dealing with incomplete, missing, or noisy data. Secondly, they do not necessitate any prior assumptions regarding the data distribution. Lastly, they can accurately map complex and approximate continuous functions [41].

The layers of a neural network are typically referred to as follows:

1. The input layer of a neural network is responsible for receiving the input data. In this layer, each input is represented by a single neuron.
 2. Hidden layers refer to the intermediate layers between the input and output layers. The term "hidden" is used for these levels since they do not directly interact with the input or output. Each layer comprises many units, often known as neurons, and is intricately related to the previous and next layers.
 3. The output layer of a neural network generates the outcomes by processing the signals received from previous layers. Each unit inside this layer is denoted by just one output that signifies a distinct value or classification [34]
- **RNN** is a term for "recurrent neural network," a specific neural network for handling sequential input. Recurrent Neural Networks (RNNs) possess recurrent connections, enabling the network to keep its internal state and facilitate the exchange of information across several phases in the sequence. RNNs excel at handling sequential data and are used for tasks such as text generation, machine translation, speech recognition, and time series forecasting. Recurrent neural networks (RNNs) have found extensive application in the research and prediction of stock market trends. They have demonstrated potential for capturing temporal connections and financial time series data patterns [42].

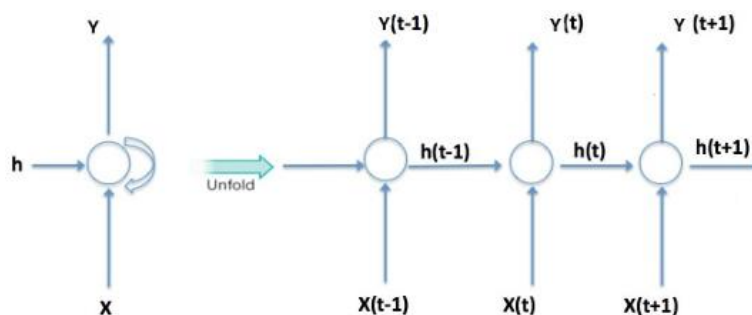


Figure 3.4: Recurrent Neural Networks.[38]

• **CNN Or CNNs:** Belong To The Category Of Discriminative Deep Architectures Furthermore, they have demonstrated commendable proficiency in handling two-dimensional data characterized by a grid-like structure, such as photos and movies. CNNs are designed based on the functioning of the visual cortex in animals. During the 1960s, Hubel and Wiesel [43]. (CNN) comprises multiple layers that collectively facilitate the extraction and manipulation of information. Below are several fundamental layers commonly used in a convolutional neural network (CNN):

1. **Convolutional Layer:** This layer employs convolutional procedures to extract features from the input data. The input data undergoes a process of extracting significant features using a weight matrix.
2. **Pooling Layer:** This layer reduces the dimensions of the extracted data from previous layers by pooling the data through techniques such as max pooling or average pooling. This reduces sensitivity to minor spatial modifications and reduces dependence on useless data.
3. **Fully Connected Layer:** The subsequent layer utilizes the features extracted from the previous layers and carries out classification or inference tasks. Each neuron in this layer is connected to every neuron in the preceding layer [20].

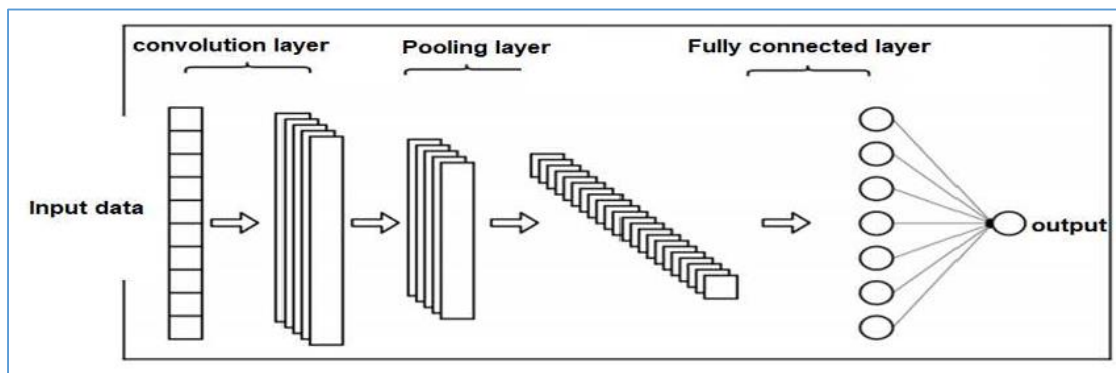


Figure 3. Structure of a CNN [27]



- **The Attention Mechanism** is a technique used in neural networks to help the models to focus on relevant input data components. It is widely used in areas like natural language processing, time series forecasting, and machine translation. The attention mechanism works by calculating the attention weights for each of the components of the inputs, using a specific query value. Later, these attention weights are used to collect the important inputs. To get the probability distribution of the weights, an activation function such as softmax is applied to the query values. [44]. Generally, the attention method involves picking the inputs that require greater focus and extracting key elements to acquire significant information. It assists models in directing their attention towards key elements and enhances their ability to manage extensive information [45] .

EVALUATION METRICS

Several criteria are employed to assess the performance of the model [30,32]:

- 1- Mean Absolute Error (MAE) and is a predictive error measure. It is computed as the summation of the absolute value of the differences between the predicted and the actual values. MAE stands for the average error between predictions and true ones and thus is evaluated in the same units as the original data. A smaller value of MAE shows more accurate prediction by the model.

$$MAE = \frac{\sum_{i=1}^n |forecast_i - actual_i|}{n} \quad (3)$$

- 2- Mean Squared Error (MSE) is squared root of average error as a loss function for minimizing square regression. In addition, it is the sum of the differences between the variables of expected and actual, divided by the number of data points above all data points..

$$MSE = \frac{1}{n} * \sum_{i=1}^n (actual_i - forecast_i)^2 \quad (4)$$

- 3- Root Mean Squared Error(RMSE). It is used to calculate the differences between expected model values and observed values at the same level. It is a common metric for training and evaluating models, providing a measure of how well the model fits the data. RMSE is closely associated with the training and assessment databases.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (forecast_i - actual_i)^2}{n}} \quad (5)$$



- 4- Mean absolute percentage error (MAPE) . It is a widely used metric in Key Performance Indicators (KPI) for stock market forecasting. It calculates the average percentage error by summing the absolute individual errors divided by the demand.

$$MAPE = \frac{1}{n} * \sum_{i=1}^n \left| \frac{\text{actual}_i - \text{forecast}_i}{\text{actual}_i} \right| \quad (6)$$

DISCUSSION AND ANALYSIS OF RELATED WORK

The ability to predict the future direction of the stock price is of immense importance not only to the business society but also to the academic society. Since the nature of the stock price information is vague and tends to be chaotic, trying to predict the tendency of the stock price is very difficult. Therefore, machine learning and deep learning strategies have become viable methods for this end. There are also some researches that employed a combination of the above methodologies in the stock market to enhance the extent of prediction. The most used approaches for getting accurate stock market forecasting are Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN). Besides, using such strategies as sentiment analysis, customer segmentation, and product recommendation can improve the overall effectiveness of the campaigns, conversion rates, and sales. Also, the use of AI and ML in marketing can help improve the satisfaction level of customers as a result of better customer engagement and the use of chatbots and virtual assistants for instant support. In this case, other performance evaluation metrics like MAPE, RMSE, MAE, and R-squared values are often applied to evaluate the efficiency of these models. There are so many methods which can be used to forecast stocks and shares prices. Some of these techniques have achieved enhanced predictions accuracies and these include; Holt-Winters, RNN, and RS which have achieved accuracies of 98%. Other techniques have resulted in moderate or low accuracy like, SVM and GAN-FD, which has an accuracy of 52 percent. There are also other techniques that enhance the performance of the predictions using technical indicators, news, or charts. Furthermore, there are other techniques that have achieved different results in predicting stock prices. Some have achieved high accuracy, such as GAN, LSTM, CNN, ARFIMA, MLP, LSTM, Autogluon, CNN-LSTM, RNN, and RS, with accuracy surpassing 90%. There are also techniques that have achieved moderate or low accuracy using metrics such as MAPE, RMSE, MAE, and R-squared, as mentioned in Table (3), such as SVM, GAN-FD, DSCNN, CBAM, BiLSTM, GA-CNN, GRU, PCA, RFE, DAE-BP, and GCN.



Table.3 Reference with performance metrics

Ref.	ACCURACY	RMSE	MAPE	R2	MAE	MSE	RMSRE	RMA5	SMAP
[1]	98%								
[2]		< 50							
[3]	53%		0.96						
[3]			< 2%						
[4]	52%								
[5]			0.0130						
[6]		65.08%							
[7]									
[12]	92.5%								
[11]	95%								
[13]		0.0316	2.1543		0.0010	0.0269			2.9597
[17]	59.25%								
[18]		11.245	5.113%		6.824				
[19]	94%								
[20]	73.74%								
[21]				0.979					
[22]	97%								
[22]	97%								
[23]	57.2%								
[25]			0.635						
[26]									
[27]				98.97					
[28]					6.94%	0.043			
[29]				> 0.9950					
[30]				0.8909	-				

Conclusions:

This paper analyzes AI and ML technologies' potential in marketing, focusing on their ability to generate insights from large amounts of data. It emphasizes the importance of market stabilizing mechanisms to enhance investor confidence and ensure market stability. The study aims to improve the current stock market system, develop prediction strategies, and create intelligent automated systems.

Acknowledgement

This study supported by computer science department, college of science for women, Babylon university.



Conflict of interests.

There is no conflict interest

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الخلاصة

سوق الأسهم، المعروف بطبيعته غير المتوقعة وعملياته المعقدة، كان محور دراسات كبيرة. غالبًا ما تفشل النماذج التقليدية في التقاط الطبيعة المعقدة والمتنوعة لسلوك سوق الأسهم بشكل كامل. مع زيادة تعقيد الأسواق المالية، هناك طلب متزايد على استراتيجيات متقدمة يمكن أن تقدم توقعات دقيقة ورؤى أساسية للمستثمرين. هناك العديد من الدراسات في هذا الصدد، منها اخترنا 24 دراسة حديثة. العام 2018 إلى العام 2023 بطرق مختلفة للخروج بنتائج تكون محور بداية جديدة في التوقعات. جمعت هذه المراجعة طرق تعلم الآلة المختلفة وتقنيات التعلم العميق، بما في ذلك الشبكات العصبية العميقة، التي تم استخدامها لبناء نماذج توقع قوية. دمج نظرية التمويل السلوكي مع المؤشرات الكمية والأخبار المالية يوفر نظرة فريدة على ديناميكيات سوق الأسهم. أيضًا، يسلط فرضية السوق الكفاءة (EMH) الضوء على التأثير الكبير للمعلومات المستقبلية، مثل الأخبار، على تقييم الأسهم. يمثل دمج تقنيات التعلم العميق في التوقع ودراسة سوق الأسهم مرحلة أساسية في البحوث المالية، يوفر فهمًا أعمق لتعقيدات ديناميكيات سوق الأسهم. ومع ذلك، لا يزال هناك عقبات يجب التغلب عليها، ومن الضروري توخي الحذر عند تطبيق الدقة المذكورة على الأوضاع التجارية الفعلية. يقدم التقارب بين التمويل السلوكي وفرضية السوق الكفاءة وتعلم الآلة العميق فرصًا لمزيد من الاستقصاء، مما يوفر طريقة أكثر شمولًا لتوقع اتجاهات سوق الأسهم.

الكلمات المفتاحية: التنبؤ بسوق الأوراق المالية; التعلم العميق ; تحليل المشاعر; الأسواق المالية; استراتيجيات التداول.