A Systematic Analysis of Stock Prediction Models using Artificial Intelligence Approaches

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Abstract- Stock market trading is an activity in which investors need fast and accurate information to make effective decisions to increase their profit. Since many stocks are traded on a stock exchange, numerous factors influence the decision-making process. Moreover, the behaviour of stock prices is uncertain and hard to predict because the stock market can easily fluctuates to different styles in overtime period. For these reasons, stock price prediction is an important process and a challenging one. This leads to the research of finding the most effective prediction model that generates the most accurate prediction with the lowest error percentage. Over the past decades, the Deep Learning (DL) algorithms has been developed to predict the stock market performances. DL models can assists the investors to predict the future movements in stock market, increases their profit rate, takes right decision with earlier time response, minimise their risk in both investment and management to achieve better performance in their securities investment. In this paper, the background of stock market detection techniques is studied to encourage further research in this field. First, the review is planned to investigate the various DL algorithms for stock market prediction system. Next, the merits and demerits of every framework are analyzed based on its performance. Finally, potential improvements are suggested to realize greater efficiency in predicting the stock market.

Indexed Terms- Stock Market Trading, Investors, Decision-Making Deep Learning, Accurate Prediction.

I. INTRODUCTION

An advancement in the fundamental aspects of information technology over the last few decades has altered the route of businesses. As one of the most captivating inventions, financial markets have a pointed effect on the nation's economy [1]. In recent days, stock trading has become a centre of attention in business lines, which can largely be attributed to technological advances. The stock market is the collection of markets where stocks and other securities are bought and sold by investors. Publicly traded companies offer shares of ownership to the public, and those shares can be bought and sold on the stock market [2]. Investors can make money by buying shares of a company at a low price and selling them at a higher price. The stock market is a key component of the global economy, providing businesses with funding for growth and expansion. It is also a popular way for individuals to invest and grow their wealth over time [3]. Each and every investor wants to predict the future value of stocks, so there is no shortage of stock market predictions by self-styled experts in the media and published by brokers or by any investment advisors [4].

A stock market prediction is an attempt to forecast the future value of an individual stock, a particular sector or the market, or the market as a whole [5]. Stock market prediction methods are divided into two main categories like technical and fundamental analysis. Technical analysis focuses on analyzing historical stock prices to predict future stock values (i.e. it focuses on the direction of prices). On the other hand, fundamental analysis relies mostly on analyzing unstructured textual information like financial news and earning reports [6]. The accurate prediction of share price movement will lead to gain significant profits for investor.

The stock market's movement is one of the most challenging issues to predict due to various factors like sentiments and expectations of traders, macroeconomic conditions, government policies, interest rates, economic growth and major events of listed companies. All of these characteristics have a significant impact on stock price predictions and makes it very difficult to predict stock prices accurately [8]. Also, stock investment is a major financial market activity, a lack of accurate knowledge and detailed information would lead to an inevitable loss of investment. The prediction of the stock market is a difficult task as market movements are always subject to uncertainties [9]. Statistical and econometric models are generally used in traditional stock price prediction but these methods cannot deal with the dynamic and complex environment of the stock market [10, 11].

In present times, the Artificial intelligence (AI) plays a significant role in the prediction of stock market prices [12]. Artificial intelligence has the potential to vastly improve stock market predictions by facilitating the rapid and precise study of massive data sets. Investors can improve their decision-making, lower their risk exposure, and boost their profits with the help of AI-powered tools [13]. AI is of two categories: Machine Learning (ML) and Deep Learning (DL). Both these ML and DL models can effectively use to evaluate the stock markets process, helps to figure out patterns of data, measure the investment risk, or predict the investment future. Some ML models like Support vector Machine (SVM), can accurately predict the future financial outcome for the stock market prediction [14]. However, there is a constraint to such algorithms, when an input data is presented to ML algorithms in a continuous range, the accuracy of the models decreases. Additionally, it takes longer time to train the larger datasets owing to time complexity [15]. The figure 1 depicts the structure of ML and DL model.

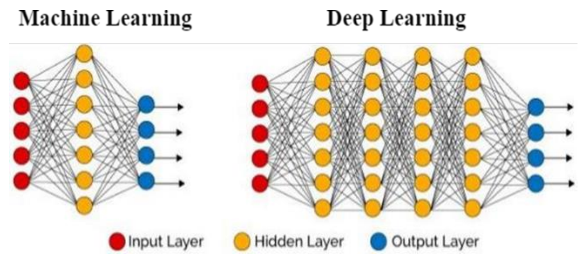

Figure 1 Structure of ML and DL model

The Deep Learning (DL) based models have been greatly enhanced the prediction achievements in various domains such as business, trading, health, agriculture, and educational data as well [16]. DL algorithms are classified as Deep Neural Network (DNN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short Term Memory (LSTM), Q-learning etc., DL attempts to model complex abstractions in data by using a multiple-level architecture most commonly of neural networks, and non-linear transformations in its algorithm [17]. In stock market prediction, DL models has rapidly emerged as a powerful tool in order to model and predict the volatile stock markets worldwide and helps to manage the investment efficiently [18]. DL models assists the investors make better decisions in both investment and management to achieve better performance of their securities investment. Also, it helps to make right decision within timely response on large data and also useful for analysing the direction of stock market indexes to predict the movement of the stock market price and increases the profit rate [19].

The main purpose of this paper is to provide a broad overview of the recent trends and advancements in DL-based stock prediction models for customer user preference analysis to improve the profit rate of the investor and managements in the field of trading. The major advantages and drawbacks of each algorithm are then discussed according to the assessment metrics. Finally, possible enhancements are highlighted to boost the accuracy of predicting the stock market prices. The rest of the sections are prepared as follows: Section II discusses various models designed to trace and predict the stock market. Section III provides the comparative analysis of those models. Section IV summarizes the entire study and suggests the upcoming scope.

II. SURVEY ON DEEP LEARNING BASED STOCK PREDICTION

Ji et al. [20] developed DL based stock price prediction method which integrates Doc2Vec, stacked auto-encoder (SAE), wavelet transform and LSTM model. This model integrates traditional stock financial index variables and social media text features as inputs of the prediction model. Then, Doc2Vec was used to train financial social media documents to extract text feature vectors. Then, SAE was adopted to reduce the dimension of text vectors for eliminating the imbalance between text features and financial features. Moreover, haar wavelet transform was applied to transform the target stock price value and to remove the random noise in the stock price time series data. Finally, stock finance features and extracted text features were fed into LSTM for stock price prediction.

Hsu et al. [21] presented a Financial Graph Attention Networks called FinGAT for recommending the top-K profitable stocks using time series of stock prices and sector information. Initially, a hierarchical learning component was devised to learn short-term and long-term sequential patterns from stock time series. Then, a fully-connected graph between stocks and sectors were constructed along with graph attention networks to learn the latent interactions among them. After that, a multi-task objective was implemented to jointly recommend the profitable stocks and predict the return values to generate the stock rankings for top-K profitable stock recommendations.

Al-Shaibani et al. [22] devised a privacy-preserving framework for blockchain-based stock exchange platform. In this system, the privacy of investors' accounts National Identification Number (NIN) and balance was preserved by ensuring all accounts were *k*-anonymous achieved by applying repeated anonymity for both NIN and balance. New anonymous accounts were generated and balances were splitted and distributed among the new anonymous accounts to ensure least *k* accounts was formulated to have the same balance. This process was repeated every new trading session for long-term unlinkability. Then, blockchain ledger updates with new anonymous accounts which was authorized by approving the entities. A non-interactive protocol were developed between the investors and the authorized entities to create anonymous accounts without any communication overhead. The model ensures the tractability and non- repudiation properties by relying on the authorized entity to update the ledger for trading transactions.

Solares et al. [23] constructed a novel method for modelling expert knowledge through fuzzy logic that allows the investor to discard undesirable stocks. In this model, a four-stage approach was developed to comprehensively address the main activities of building stock portfolios. Then, a fuzzy logic was presented to exploit expert knowledge and eliminate (undesirable) stocks where were not convenient for investment. The multi-criteria decision adding (MCDA) method was utilized to model the expert knowledge and analysis the performance of a given stock for efficient eliminating the undesirable stocks.

Ansari et al. [24] developed a deep reinforcement learning (DRL)-based decision support system for automated stock market trading. Initially, the data from different stocks were collected. Then, Deep-Q Network (DQN) was used to observe the stock market situation which includes the historical trends of the stock prices. The future trends were monitored concurrently using forecasting network at each time step whose output was concatenated with past trends of stock prices. The RL agent maps the state to action-value pairs or takes trading decisions to fully observe the financial time series data. Moreover, Gated Recurrent Unit (GRU) agent was utilized which captures more informative and inherent aspects of time-series financial data for stock prediction.

Koo et al. [25] developed a hybrid prediction model by integrating Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models with a distribution manipulation Strategy using LSTM Networks for Stock Market Volatility. In this model, a root-type functions was used to transform left-biased and pointed distribution of original volatility to a volume-upped (VU) distribution shifted to the right for the filtering tasks. Then, LSTM was employed to improve the prediction performance in the right domain region of label probability density by making the prediction distribution comparable to the label distribution for stock market volatility.

Kim et al. [26] Suggested a portfolio management framework called ASA for Autonomous Stock selection and Allocation. In this model, the simple graph- and hypergraph-based ranking models were hybridized to select the most profitable stocks for relational modelling. Then, the classification and regression models were integrated to determine the investment ratio for stock allocation. In addition, ASA extracts features using hierarchical clustering and feature selection models and captures temporal information by LSTM, Bi-directional LSTM (Bi-LSTM), and the Hawkes attention mechanism for financial and economic data ton predict the stock prices.

Zhang et al. [27] presented a novel dynamic parameter optimization algorithm using reinforcement learning (RL) model for stock prediction and trading. In this method, an abundant feature set was designed to train the price trend model. Then, a rolling model was used to generate an adaptive trading framework for stock price trend prediction. An Inverse RL algorithm was devised for parameter learning of reward function and constraint item of stock

$T+\ 1$ rules was considered in the operation of reward function. Finally, a reward-enhanced upper confidence bound (UCB) selection algorithm was used to automatically optimize the parameters of the trading logic in real-time trading. Moreover, high-frequency trading framework was deployed into a production level system and greatly increase the stock profit rate. Wei et al. [28] developed an adversarial game neural network (AGNN) model using LSTM and attention mechanism for stock ranking prediction. In this model, the attention LSTM (ATT- LSTM) was used to extract the time series features to maintain the real ranking relationship by directly fitting the attention mechanism. Then, different trading tasks were integrated to construct a mean square-weighted ranking error (MS-WRSE) loss function for ranking the stock values and to optimize the network. The AGNN model was used to eliminate the influence of market-style factors using the mutual game between the main neural network and the auxiliary neural network for on stock ranking predictions.

Rekha et al. [29] developed a cooperative DL model for stock market prediction using deep auto encoder and sentiment analysis. In this method, the auto encoder was used to denoise the historical stock data, and the denoised data were transferred into the DL model along with news sentiments. The stock data was concatenated with the sentiment score which would be fed into the LSTM/GRU model for output prediction of stock prices.

Srivinay et al. [30] suggested a hybrid stock price prediction model based on prediction rule ensembles (PRE) and deep DNN model. Initially, stock technical indicators were considered to identify the uptrend in stock prices. The moving average technical indicators was utilized to identify the trend in the stock and helps to eliminate the random behavior of the stock price. Then, PRE technique were used to select the rules with the lowest root mean square error (RMSE) score. The three-layer DNN was considered for stock prediction. Huang et al. [31] constructed a Multilevel Graph Attention Model (ML-GAT) for stock prediction. In this model, LSTM and Bidirectional Encoder Representations from Transformers (BERT) module was applied to learn the feature representation of data and embedded them into the stock graph to predict the trends of related stocks. Then, ML-GAT was used to selectively filter the different types of information to form an aggregated graph through multiple layers of attention mechanisms at different levels to learn the feature representation of nodes to formulate the accurate predictions. This model effectively leverages the stock network graph topological information and market characteristics to facilitate the stock prediction tasks

Cui et al. [32] presented a multi-scale CNN (MS-CNN) model for stock data to efficiently extract the stock trend features and make better decisions to analyse the stock market This model was divided into two stages In the first stage, data from the raw daily prices like open price, highest price, lowest price, close price, and trading volume are processed by deep CNN (DCNN). In the second stage, the DRL algorithm was executed in which the agent observes the state, then executes the action resulting from its policy and receives corresponding rewards. Finally the agent would generate the optimal trading strategy by interacting with the environment in the DRL framework.

Mu et al. [33] constructed a Multi-Source data with Sparrow Search Algorithm and LSTM (MS-SSA-LSTM) for the prediction of stock prices. Initially, an east Money forum posts information was crawled to establish the unique sentiment dictionary and compute the sentiment index. Then, the SSA was used to optimize the LSTM hyperparameters which objectively determines the model parameter settings and improves the prediction effect. Finally, the sentiment index and fundamental trading data were integrated, and LSTM was used to forecast stock prices in the future actions.

Lee et al. [34] presented an effective exploitation of macroeconomic indicators for stock direction classification using the multimodal fusion transformer. In this method, the multimodal early fusion method was utilized to learn the intermodality correlation of features. In this early fusion method, all the modalities were processed through the scaled dot-product attention together to learn the relationship between data in the early fusion method. The in- depth analysis was conducted to identify the proportion of the stocks numbers, and how well the stocks in each sector perform in prediction tasks. Also, this analysis utilizes the fusion strategy which indicated that an early fusion strategy provides the best prediction performance than the late fusion strategy in group of stocks prediction performances.

Xu et al. [35] presented an enhancement economic system based-graph neural network in stock classification. In this model, the graph convolutional semi-supervised model (PA-GCN) was developed by combining graph attention mechanism and Elu activation function. PA-GCN effectively compensates the poor learning before the data enters the convolutional layer and can more effectively complete the classification by calculating the weights for the input data in advance. Then, the Dropout layer was added at the end of the model to prevent the model from overfitting issues during the training time for stock classification.

Choi et al. [36] developed a hybrid information mixing module for stock movement prediction. In this model, time-series and semantic features were extracted by embedding the two data types using the GRU and BERT methods. A mixed feature was created containing multimodal information combining the two features, reflecting the unique characteristics of each data type. The hybrid information mixing module consists of feature and interaction mixing multilayer perceptron (MLP) was developed to predict stock price movement by capturing market signals that affect stock price fluctuations. The mixed feature takes the hybrid information mixing module as input and it was double-learned for each row and column to predict stock price movement.

Xu et al. [37] developed a graph convolutional neural networks (GCNN) model for financial stock classification and financial market development. In this model, an information of all GEMstock was identified using crawler technology to understand the trade management. A multi-source heterogeneous graph which composed of stock nodes and related word nodes was utilized to extract an important information and external node extension information by enabling the stocks categorization using GCNN. This model employs two layers of convolutional layers and activation functions to effectively categorize stocks and expand stock features to classify GEM stock categories.

Zhang et al. [38] developed a stock price prediction model using CNN-BiLSTM-Attention Model to enhance the accuracy of predicting stock prices and indices. First, CNN was used to extract the nonlinear local features of stock data. Then, BiLSTM was used to remove the bidirectional time series features of the sequence data. Finally, the attention mechanism was used reduce the impact of redundant information by assigning greater weights to more important feature components through the automatic fitting of weight assignments to the information features extracted by the BiLSTM layer to improve the stock price prediction accuracy.

III. COMPARTIVE ANALYSIS

In this part, a comparative study is presented in Table 1 according to the benefits and drawbacks for stock market prediction using different DL methods which are briefly studied in above section are listed below.

Table 1. Comparison of various DL methods for stock market prediction

Ref No	Methods	Advantages	Disadvantages	Performance
[20]	Doc2Vec, SAE, Haar wavelet Transform and LSTM.	This model utilizes investor sentiments to improve the to improve prediction performance greatly with lower computational complexity	This model was less representative as it predicts single stock price from single social media platforms which were not possible for larger companies	MAE = 0.019, RMSE = 0.110, R^2 = 0.957
[21]	FinGAT, hierarchical learning component and fully- connected graph	This model effectively generate promising recommendation Performances without using sector information.	It does not provide any constructive structure to analyse stocks/sectors, which was severely influenced by one another in data training	Mean Reciprocal Rank (MRR) = 0.89 Accuracy = 74.37%; Precision = 67.21%
[22]	Anonymity, blockchain ledger and -interactive protocol	This model results in high level of anonymity with acceptable transactions execution time overhead	When the number of the newly generated anonymous accounts was high, the execution would be increased	Average K-anonymity = 358,439; Total execution time = 3.073.3s; Total difference time = 43.4%

				Total number of transactions = 1,075,317;
[23]	Fuzzy Logic and MCDA	This model reduces the computational complexity in the search process and likely improves the final stock portfolio performance	Lower results on larger datasets	Standard deviation = 3.54% Discarding stocks with fuzzy logic = 86.14%
[24]	DRL, DQN and GRU	This model was tested with different stock market which provides better profit values while trading	The collected information was not valued properly	Sharpe ratio = 0.559; Sortino Ratio = 0.607
[25]	GARCH and LSTM	This approach tries to reduce predicting errors by adjusting for earlier forecasting failures and improving the standard of ongoing forecasts.	This model results in overfitting issues.	Confidence Interval = 0.125; correlation co-efficient for α = 0.2 = 128.7

[26]	Simple graph, hypergraph- based ranking models, LSTM, Bi- LSTM,	This model was robust to noisy training data and takes less effort to prepare the data	This model requires large amount of data to train the model	Average return rate = 5.4%; Sharpe ratio = 0.61; Maximum drawdown = 0.09;
	Hawkes attention mechanism			
[27]	Inverse RL algorithm, rolling model, UCB selection algorithm and high-frequency trading framework	This method was efficient to utilize in high frequency trading system with real time trading applications	This model resulted with more overfitting issues and additional data were required to trade in the secondary markets	Average commission rate = 13131; Average profit rate = 23347
[28]	AGNN, LSTM, MS-WRSE and ATT-LSTM	This model enhances the ranking relationship between stocks, which was more beneficial than general stock price prediction tasks	This model necessary rely on human prior knowledge to identify the clear potential factors as network input.	Mean Average Error Value = 1.6

[29]	DL model, Auto-encoder, LSTM/GRU	This model effectively minimizes the effect of noise in the data to complement the prediction capability of the DL model	The better structure could be illustrated for representing the relationship between the stock price and news headlines	RMSE = 0.95 MAE = 0.6470 MAPE = 1.09 $R2$ = 0.9850
[30]	PRE and DNN	DNN hyperparameters were well and it	This model considered limited technical indicators	RMSE = 7.20 MAE = 8.55
		was more robust to noises	leads to instability in the performance	
[31]	LSTM, BERT and ML-GAT	This model's stock connections were consistent towards real-time interactions	High computational cost	Accuracy = 95% F1-Score = 95%

[32]	MS-CNN, DCNN and DRL	This model provides good trading strategy for long-term profits.	It selects over-estimated value in some cases leading to longer training time.	Profit = 6,98,228.67 Sharp ratio = 1.678; Annualized Ratio = 82.95;
[33]	SSA and LSTM	The model automatically outputs a stock price trend chart and forecasts the stock price for the following day.	This model needs to concentrate more on sentiment analysis to analyse more emotional indicators for stock price forecast	Root Mean Square Error = 0.123; Mean Absolute Error = 0.091 Coefficient of Determination ($R2$) = 0.956
[34]	Multimodal Early Fusion Method And In-Depth Analysis	The convergence rate of this model was efficient.	This model performed with limited number of datasets and results in time complexity.	Classification accuracy of early fusion method = 1.42 and late fusion = 1.52
[35]	PA-GCN, graph attention mechanism and Elu	This model's generalizability rate is quite high.	This model exhibited high level of temporal and spatial complexity.	Classification accuracy on Cora dataset = 81.69%;

	ıctivation function			Classification accuracy on Stock nodes = 81.2%
[36]	ĢRU, BERT ınd MLP	This model effectively captures the correlation of dynamic markets status	This model necessitates additional data to analyse the influence of Variables that affects stock market volatility	Accuracy = 69.20%; MCC = 0.43 ; and F1 score = 76.175
[37]	ĢCNN and crawler technology	This model have better decision interpretation with easy training process	This model results in ineffective performances on larger dataset	Accuracy = 83.04%; F1-Score = 83.03%
[38]	ĊNN, ЗiLSTM, and Attention Mechanism	This model determines the certain degree of generalizability prediction in stock price prediction	This model results in high time and space complexity	MAPE = 1.13 RMSE = 7.13 $R2$ = 0.987

From the above table, the article [20-38] is studied and it is concluded that the article [31] yields better prediction result for stock market prediction. In article [31], the data financial markets, news, and corporate relations of stock were incorporated into graph neural attention network-based model by utilizing the feature extraction module in order to compensate the lack of prior knowledge of existing stock forecasting methods. ML-GAT effectively filters the different data types to construct an aggregated graph through multiple layers of attention mechanisms at different levels to learn the feature representation of nodes to enhance the prediction performance. In addition, BERT was applied to the financial field to learn the feature representation of collected data and embedded them into the stock graph and explore the node representation by BERT which was more beneficial for stock price prediction.

CONCLUSION

Stock is a financial product characterized by high risk, high return and flexible trading, which is favoured by many investors. Investors can get abundant returns by accurately estimating stock price trends. Since many stocks are traded on a stock exchange, numerous factors influence the decision-making process. Moreover, the behaviour of stock prices is uncertain and hard to predict. For these reasons, stock price prediction is an important tasks and determine the accurate prediction with the lowest error percentage on stock prices. DL models are current popular methods utilized for stock price prediction and helps the investors to make better decision in stock market forecasting. This article conducted a comprehensive review of different DL methods for stock market prediction according to their strengths and weaknesses and prediction efficiencies. Thus, this review can help researchers to select the most efficient and reliable predictive methods to enhance the accuracy in stock prediction. So, future research will focus on reducing the time series analysis-based stock market prediction systems using large number of data.

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