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Exploring Deep Learning Approaches for Stock Market Forecasting

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Abstract—*Forecasting stock market values is a crucial task for economists, financial analysts, and investors. However, it is also a challenging one due to the stock market's complex, non-linear, unpredictable, and seasonal nature. Deep learning models have shown significant potential in predicting stock prices, but creating a model that can accurately adapt to these characteristics remains a challenge. In addition, the selection of relevant data, including historical stock market data and investor sentiments based on financial news and tweets, is crucial for accurate predictions. Researchers have employed various methods and models, such as technical and fundamental analysis, to predict stock values. However, the inability of statistical and deep learning models to account for market dynamics and external factors, such as political, social, and investor emotions, limits their generalizability. Therefore, a new approach is needed to improve the accuracy of stock market predictions. Facebook's recent creation of the Prophet model has shown promising results in accurately fitting trends and seasonality. The model is based on a decomposable time series forecasting model with additive components, making it an effective tool for capturing complex patterns in time-series data. However, the Prophet model does not capture the relationships between different variables in the data. To address this limitation, we propose an Attention Based Stacked LSTM model that leverages the Prophet model's strengths and enhances the learning process. The proposed model uses attention mechanisms to highlight the relevant features in the input data, making it more effective in capturing significant relationships between variables. We plan to test the proposed model using financial news data and historical stock price data to demonstrate its high potential. This will enable us to develop a more accurate and robust model for predicting stock market values.*

1. INTRODUCTION

The stock market is a dynamic and complex system that is constantly influenced by a variety of factors. Predicting its future performance can be challenging, but with the rise of data-driven techniques, it is now possible to make more informed predictions. By using ML algorithms to analyze vast amounts of historical stock market data, patterns and relationships identification is possible that can help predict future trends. This approach has the potential to provide investors with a valuable tool for making informed decisions and improving their returns.

Due to a variety of elements, including social, psychological, political, and economic impacts, forecasting the stock is challenging. In addition to being time-sensitive and nonlinear, stock market data makes predictions even more difficult. Despite these challenges, stock market prediction is critical for success in the stock market [1]-[2]. Without adequate information and knowledge, investors are at risk of incurring significant losses . Conventional methods for stock price prediction, such as Fundamental Analysis and Technical Analysis, were widely used prior to the advent of computational methods for risk analysis [3].

Fundamental Analysis - Fundamental analysis is a method of stock value evaluation by analyzing various financial and economic factors such as a company's financial statements, management quality, industry trends, and economic conditions [4]-[5] as shown in Fig. 1. An undervalued or overvalued stock can be identified by calculating its inherent value and evaluating it to its current price on the market. The belief is that a company's underlying financial and economic indicators can provide insight into its future performance and potential for growth, leading to investment decisions.

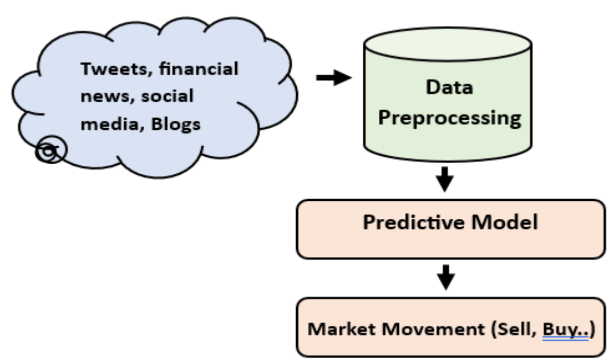

Fig. 1: Fundamental Analysis

Technical Analysis - Technical analysis is a method of evaluating securities by analyzing statistics of market activity, such as volume and past prices [6]. Technical analysts believe that market trends, as shown by charts and other technical indicators, can predict future activity. They look for patterns in price and volume movements to identify buying and selling opportunities. As the Fig. 2. shows technical analysis is based on the idea that market trends, as shown by charts and other technical indicators, tend to repeat themselves and that these patterns can be used to make investment decisions [7]. Technical analysis does not consider a company's financial or economic fundamentals, but rather focuses solely on price and volume data.

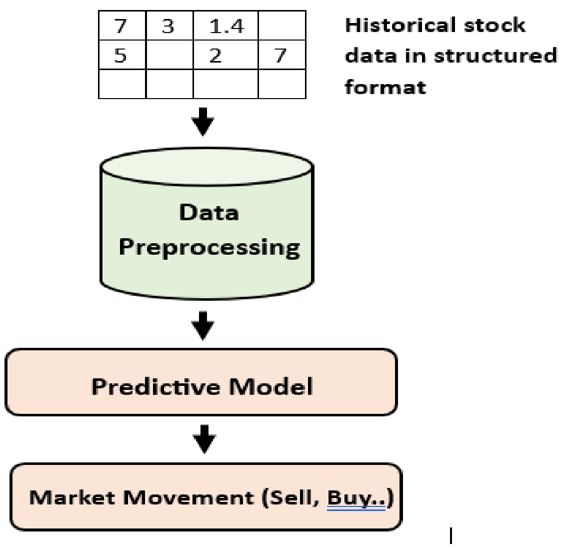

Fig. 2. Technical Analysis

2. STOCK MARKET CHRONICLES

2.1 Stock Market Importance

The economy and the financial sector both heavily depend on the stock market. By providing a platform for investment, it allows individuals and institutions to put their money to work and potentially earn returns. This also leads to capital formation, as companies can raise capital for growth and expansion by issuing and selling shares to the public [8]. The stock market can also serve as an indicator of a country's overall economic health and stability, as changes in stock prices can reflect the overall sentiment of the economy [9].

The stock market helps determine the fair value of a company's shares by bringing together buyers and sellers in a competitive marketplace, a process known as price discovery. By investing in the stock market, individuals can build wealth over time as companies grow and their stock prices increase [10]. It is also a popular option for retirement planning, as stocks offer the potential for higher returns than other investments like bonds. Finally, companies listed on the stock market often use their capital to create jobs and stimulate economic growth, making it an important factor in job creation.

2.2 Unprintability of Stock market

The stock market is inherently unpredictable and can be affected by various factors. Economic and political events such as changes in the global economy and government policies, as well as geopolitical events, can have a major impact on the stock market [11]. Company-specific events such as earnings reports, management changes, and competition can also impact the stock prices of individual companies. Market psychology, which is heavily influenced by investor sentiment and emotions, can be difficult to predict and can lead to sudden changes in market behaviour [12]. Changes in interest rates can also impact the stock market, as higher interest rates can reduce consumer spending and hurt corporate profits. Additionally, unexpected events such as natural disasters, cyber-attacks, and outbreaks of disease can also impact the stock market unpredictably. Due to these factors, it is important for investors to have a long-term investment strategy and not to base their decisions solely on short-term market movements [13].

Due to these unpredictable factors, the stock market can experience rapid fluctuations and be difficult to forecast with certainty. This is why it's important for investors to be aware of the risks involved and to diversify their portfolios to manage these risks.

2.3 Ground Works

Getting started in the stock market requires a solid foundation. First, you should develop an investment strategy that aligns with your financial goals, risk tolerance, and time horizon [14]. Then, it is important to educate yourself on the stock market and basic investing principles. To begin investing, you will need to open a brokerage account with a reputable firm. Researching and analysing potential investments using both fundamental and technical analysis will help you make informed decisions about which stocks to buy [15]. Diversifying your portfolio across different types of stocks and sectors can help reduce risk. Regular monitoring of your investments is important to make any necessary adjustments based on market conditions and changes in your financial goals [16].

3. RESEARCH TAXANOMY

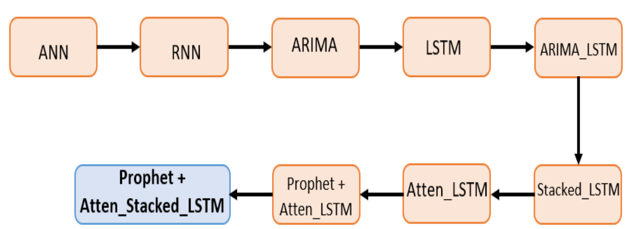

Fig. 3. Research Taxonomy

The next section summarizes the individual articles in each research taxonomy category as illustrated in Fig. 3, highlighting their distinct model, dataset, deep learning methodologies and contribution.

3.1 RNN

RNN stands for Recurrent Neural Network, which is a type of neural network designed artificially for processing sequential data. Unlike traditional feedforward neural networks, RNNs have loops in their network structure that allow them to retain information from previous steps in a sequence and use it to inform their output at a later step. This makes RNNs well-suited for tasks such as NLP, speech recognition, and time series forecasting.

Jiang et al. [17] created a recurrent neural network (RNN) to capture the interplay between financial information's cross-domain and inner-domain. Their model was put to the test, and it was shown to outperform a straightforward RNN and Multi-Layer Perceptron (MLP) in terms of making predictions about the stock market and currencies.

In 2017, Deng et al. [18] enhanced the recurrent neural network (RNN) model to incorporate the fuzzy learning idea. They claim that their RNN model is the most effective after comparing it to various Deep Learning (DL) models including CNN, RNN, LSTM.

In 2017, Almahdi and Yang [19] devised a superior portfolio by combining RNN and Reinforcement Learning (RL). The results show that the suggested trading method can handle transaction costs well and routinely beats hedge fund benchmarks.

3.2 ARIMA

A statistical technique for time series forecasting called ARIMA (Autoregressive Integrated Moving Average) models the relationship between an observation and several preceding data. It combines moving average (MA), difference (I), and autoregression (AR) components. In order to find and extract significant patterns in time-series data and base forecasts on these patterns, ARIMA models are utilised. In disciplines including economics, finance, and weather forecasting, ARIMA is extensively employed.

A novel Attention-based Recurrent Neural Network (ARNN) incorporating wavelet denoising in the input was presented by Zeng in 2020 [20]. The forecast was produced by integrating the results of the ARNN model with the Autoregressive Integrated Moving Average (ARIMA) method.

Y. Wang, Y. Guo, [21] offers a combined model of XGBoost and ARIMA to analyze time series data on stock market volatility. The model combines XGBoost's ability to handle non-linear correlations and interactions between variables with the capabilities of ARIMA in detecting seasonality as well as trend. The research demonstrates that the suggested model performs better in terms of forecasting accuracy than existing forecasting models and offers accurate and timely volatility forecasts for financial risk management. For investors and financial institutions, the mixed ARIMA-XGBoost model can be a useful tool for decision-making and risk management in the stock market.

Y. Du, [22] examines how well an ARIMA-BP neural network model combination can forecast the stock price indices. The authors use BP neural network to record non-linear correlations and exchanges between parameters, and ARIMA to capture linear connections among the factors. They test the model's effectiveness using actual data, and they discover that the coupled ARIMA-BP neural network model works better than other well-known models in terms of predicting accuracy. The study illustrates how merging several forecasting models may enhance stock market predictive ability.

3.3 LSTM

A RNN model called LSTM is used for analysing sequence data, including speech recognition, time series And natural language processing. It is designed to overcome the vanishing gradients problem encountered in traditional RNNs by introducing memory cells and gates that allow information to persist over long periods of time. This makes LSTMs well suited for tasks that require the model to maintain context and make predictions based on information from a large number of previous time steps.

Krausa and Feuerriegel (2017) [23] argued that a deep learning (DL) model may be used to transform financial statement into a decision-making procedure. LSTM surpasses conventional ML techniques as Lasso, Elastic Net, Ridge Regression, Random Forest, Support Vector Regression (SVR), AdaBoost, and Gradient Boosting, as well as Recurrent Neural Networks, according to their training and testing experiments (RNN).

Masud Rana et al. [24] The goal was to forecast Acciona's stock price that used a variety of machine learning methods, including LSTM, SVR, and regression analysis, each with a unique perceptron and optimizer. The results showed that LSTM beat some other two methods, with the activation unit and adamax optimizer as well as the tanh activation function and Adam optimizer producing the highest accurate results (98.49 percent).

Xiaodong Li’s (2020) research [25] examines how to anticipate the direction of the financial markets using indicators derived from stocks and news sentiment from text-based news stories. The method comprises modelling news sentiment using sentiment dictionaries and converting previous prices into technical indicators. A fully connected neural network is applied to provide stock predictions, while a two-layer LSTM neural network is used to capture the orderly data in market snapshots. With LSTM outperforming MKL and SVM in terms of forecasting accuracy and F1 score, the results demonstrated that combining the two types of data was more effective than relying just on technical indications or news sentiment.

S. Selvin et al. [26] compares the effectiveness of RNN, LSTM, and CNN-sliding models in predicting stock prices using different hyperparameters. The study shows that LSTM and RNN models perform better than the CNN-sliding window model in terms of accuracy and precision, with LSTM slightly outperforming RNN. Increasing the no of input features and training epochs enhances the performance of all models. The authors suggest that LSTM and RNN models can be used for stock price prediction in real-world financial applications.

3.4 Stacked LSTM

Stacked LSTMs are deep learning models that utilizes multiple layers of Long Short-Term Memory units. The term "stacked" refers to the fact that these multiple layers are stacked on top of one another, allowing the model to learn increasingly complex representations of the input data. The stacked LSTM architecture has been used for a variety of time series and natural language processing (NLP) tasks because it is good at capturing long-term relationships in sequential data..

According to Rokan Uddin et al. (2022) [27], their research found that the accuracy of an LSTM model better performed than both ARIMA and linear regression models. They discovered that a multivariate LSTM model yielded even better results compared to a individual LSTM model. Furthermore, the researchers hypothesized that the multivariate Long short-term memory model's performance may be improved by using more parameters.

K. Saleh, M. Hossny et al. [28] proposes a LSTM network for analyzing the intent of vulnerable road users (VRUs) based on their motion trajectories. The study uses real-world data to train and evaluate the model and compares its performance with other popular machine learning models. The research show that the stacked LSTM network outperforms other models in context of intent prediction accuracy, providing reliable and timely predictions for VRU behavior. The proposed model can be a valuable tool for improving the safety of vulnerable road users and reducing traffic accidents.

3.5 ARIMA LSTM

ARIMA (Autoregressive Integrated Moving Average) and LSTM (Long Short-Term Memory) are two different time series forecasting methods. Combining ARIMA and LSTM is possible and can lead to improved performance compared to using only one of the methods. For instance, the LSTM component can handle the non-linear patterns whereas the ARIMA component can capture the linear patterns in the time series.

In his research, Skehinde T. (2022) [29] developed a novel approach to produce daily predictions for each series by combining a linear ARIMA model with a LSTM network. To better understand the behaviour of the series over time, he employed wavelet methods to decompose them into approximation and detail elements. He developed an ensemble model using these methods to improve the accuracy of the findings.

In the study by Lai C.Y (2022) [30], a LSTM model was proposed for stock market prediction. The model used the average of the low, open, high, volume, and close stock market information from the preceding five days as input for generating the initial prediction. The ARIMA approach was then used to include this forecast into the average stock fluctuations for the next few days. Indicators used in technical analysis were also used to determine whether to purchase, hold, or sell stocks.

Bukhari et al. [31] introduces a novel forecasting model called Fractional Neuro-Sequential ARFIMA-LSTM, which combines the ARFIMA model and Long Short Term Memory neural network to identify long-term dependencies and non-linear relationships in financial time series data. The authors pre-process the data using a fractional differencing method to improve its stationarity and apply the ARFIMA model to capture the fractional integration component and the LSTM model to capture non-linear relationships. The defined model performance is better than other models in terms of forecasting accuracy and can provide reliable predictions for financial market forecasting, making it a valuable tool for financial analysts and investors to manage risks in the stock market.

Y. Weng et al. [32] presents a mixed model of ARIMA and neural network to forecast horticultural product prices. To train and test the suggested model, the authors gathered a sizable dataset. According to the study, the hybrid model outperforms other widely used forecasting models in terms of accuracy and can provide accurate price forecasts for horticultural products. The paper suggests that the proposed model can be a valuable tool for farmers, retailers, and consumers to manage risks in the horticultural market.

3.7 Attention Based LSTM

The Attention LSTM (Attention Long Short Term Memory) uses an attention mechanism to focus on relevant parts of the input sequence when making predictions. The attention mechanism assigns a weight to each input step, indicating how important it is for the prediction task. This allows the model to automatically learn which parts of the input sequence are most relevant, rather than relying solely on the fixed-length input representation used in traditional LSTM networks.

Attention LSTMs have been shown to outperform traditional LSTMs on various sequence prediction tasks, such as machine translation, speech recognition, and time series forecasting. By automatically focusing on the most relevant parts of the input sequence, they can learn more complex dependencies and make more accurate predictions.

In their research, Chen Li and colleagues (2022) [33] compiled six variables that could have an influence on stock prices and used a LSTM and CNN model combination to forecast stock prices. An attention layer was added the model too improve accuracy and scalability. As the sequence length was longer, it was discovered that the suggested technique achieved good accuracy when compared to previous models.

Arslan S.[34] proposes a mixed time series model to improve forecasting precision. The model combines the seasonality information preserved by the Prophet model with the depersonalization of the data provided by the neural network model. The study shown that time series decomposition increases the accuracy of final predictions, and the hybrid model outperformed single models and cutting-edge methods including ARIMA, SVR, Holt-Winters, EMD-LSTM, EMDGRU. The accuracy results show that suggested model performs competitively for certain nations in the dataset while outperforming others. Fig. 4. illustrates the accuracy wise model analysis of above discussed deep learning models.

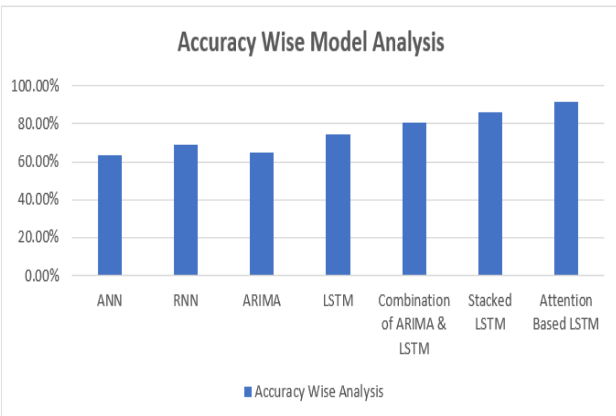

Fig. 4. Accuracy wise Model Analysis

4. PROPOSED FRAMEWORK

We suggest a novel model called "Prophet's Attention based Stacked LSTM" in our research. This model is designed to improve the accuracy of predictions in certain applications by incorporating attention mechanisms and stacked LSTM units.

The attention layer allows the model to concentrate on specific parts of the input sequence that are more relevant to the prediction, while the stacked LSTM units enable the model to capture long-term dependencies in the data [35]. Overall, the proposed model aims to enhance the performance of prediction tasks by leveraging the strengths of attention and stacked LSTM units.

Fig. 5. Shows the proposed system architecture for the Sentiment Analysis Based Stock Market Recommendation System using two phase approach. It's mainly divided into following stages :

4.1.1 Data Collection and Preparation: The first step is to collect and pre-process the data required for the analysis. This includes collecting historical stock prices and news articles related to the companies of interest. The collected data is then cleaned, transformed, and normalized to ensure that it is ready for analysis.

4.1.2 Model Development: The model development stage includes the model creation for Historical stock data and Financial news sentiment data.

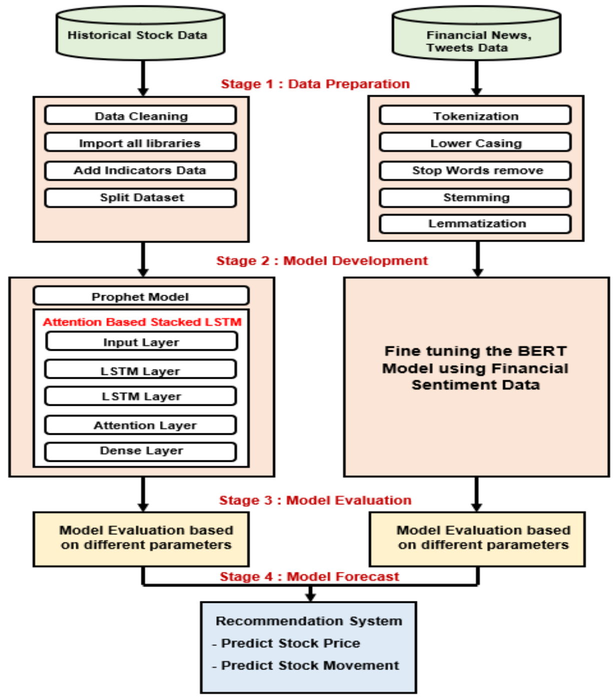

Fig. 5. Proposed Architecture

BERT Model : The pre-processed data is then used to fine-tune a pre-trained BERT model [36]. This involves training the BERT model on the financial news dataset to learn the specific characteristics of the language and to understand the sentiment of the news articles. The model is trained to classify text as either positive, negative, or neutral.

Prophet Model: This model is a time-series forecasting model that can generate predictions for future stock prices [37]. The Prophet model can capture seasonality, trends, and other factors that can affect the stock price. The preprocessed data is used as an input to prophet model.

Attention-based Stacked LSTM Model: The output from the Prophet model is then fed into the above model. This model includes the Input layer, Stacked 2 LSTM Layers, Attention Layer and Dense Layer. Based on the Numerical data, the model is trained.

4.1.3 Model Evaluation: In model evaluation stage, different parameters are used to evaluate both the models on testing dataset. Calculate the accuracy, precision, recall, F1 score, and other relevant evaluation metrics. Plot and analyse the confusion matrix to identify false positives, false negatives, and other errors. Analyse the prediction results to identify trends, patterns, and insights.

4.1.4 Model Forecast: The model forecast stage includes:
Recommendation System: Based on the predictions generated by the given models, the system can provide a recommendation for whether to sell, buy or hold the stock and also suggest the future price for a given stock..

User Interface: Finally, the user interface for the system, such as a web application or a mobile app, may be used to show it to the user. The user interface can include suggestions and other pertinent data, like historical patterns, the findings of sentiment analysis, and expected stock prices. By giving input on the recommendations, the user may engage with the system and help it get better over time.

5. CONCLUSION

This research paper analyses different techniques used for effective stock market prediction, categorizing them based on deep learning models, methodologies, datasets, performance metrics, and implementation tools. The techniques studied include ANN, RNN, ARIMA, LSTM, ARIMA LSTM, Stacked LSTM, Attention LSTM, and Prophet model. LSTM and Prophet model are commonly used for effective stock market prediction. However, accurately predicting stock market trends poses significant challenges due to its complex, non-linear, unpredictable, and seasonal nature. Relevant data selection, including both historical stock market data and investor sentiments based on financial news and tweets, is critical. The proposed model aims to overcome these challenges and provide more accurate stock market predictions.

REFERENCES

[1] S. Agarwal and N. B. Muppalaneni, "Stock Market Price and Cryptocurrency Price Prediction," in IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics, Ballari, India, pp. 1-6, 2022.

[2] S. Sridhar and Sanagavarapu, "Multi-Head Self-Attention Transformer for Dogecoin Price Prediction," in 14th International Conference on Human System Interaction (HSI), Gdańsk, Poland, 2021, pp. 1-6.

[3] A. Bozanta, S. Angco and A. Basar, "Sentiment Analysis of StockTwits Using Transformer Models," in 20th IEEE International Conference on Machine Learning and Applications, Pasadena, CA, USA, 2021, pp. 1253-1258.

[4] Segal, T. " Fundamental analysis: Principles, types, and how to use it, Investopedia. Investopedia", Available at: https://www.investopedia.com/terms/f/fundamentalanalysis.asp#:~:text=Fundamental%20analysis%20is%20a%20method,a%20buy%20recommendation%20is%20given. .

[5] Manurung, Adler Haymans & Prabowo, Hartiwi. "Algorithm and modeling of stock prices forecasting based on long short-term memory." In ICIC Express Letters, p.p 1277-1283.

[6] DailyFX (no date) "Forex Technical Analysis Data & Analysis". Available at: https://www.dailyfx.com/technical-analysis.

[7] Jigar Patel, Sahil Shah,, K Kotecha, "Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques", in Expert Systems with Applications, Volume 42, Issue 1, 2015, P.p 259-268

[8] S. Selvin, E., V. K. Menon and K. P. Soman, "Stock price prediction using LSTM, RNN and CNN-sliding window model," in International Conference on Advances in Computing, Communications and Informatics (ICACCI), Udupi, India, pp. 1643-1647, 2017.

[9] Bathla, G., Rani, R. & Aggarwal, H. Stocks of year 2020: prediction of high variations in stock prices using LSTM. *Multimed Tools Appl* (2022). https://doi.org/10.1007/s11042-022-12390-5

[10] S. Boonpeng and P. Jeatrakul, "Decision support system for investing in stock market by using OAA-Neural Network," 2016 Eighth International Conference on Advanced Computational Intelligence (ICACI), Chiang Mai, Thailand, 2016, pp. 1-6, doi: 10.1109/ICACI.2016.7449794.

[11] Strader, Troy J.; Rozycki, John J.; ROOT, THOMAS H.; and Huang, Yu-Hsiang John (2020) "Machine Learning Stock Market Prediction Studies: Review and Research Directions," in *Journal of International Technology and Information Management*: Vol. 28: Iss. 4, Article 3.

[12] Shun Chen & Lei Ge, "Exploring the attention mechanism in LSTM-based Hong Kong stock price movement prediction, Quantitative Finance", 2019, p.p 1507-1515.

[13] L. -C. Cheng, Y. -H. Huang and M. -E. Wu, "Applied attention-based LSTM neural networks in stock prediction," 2018 IEEE International Conference on Big Data (Big Data), Seattle, WA, USA, 2018, pp. 4716-4718, doi: 10.1109/BigData.2018.8622541.

[14] I. Kumar, K. Dogra and P. Yadav, "A Comparative Study of Supervised Machine Learning Algorithms for Stock Market Trend Prediction," in Second International Conference on Inventive Communication and Computational Technologies (ICICCT), Coimbatore, India, pp. 1003-1007, 2018.

[15] Choi, Hyeong Kyu. "Stock price correlation coefficient prediction with ARIMA-LSTM hybrid model." 2018 arXiv preprint arXiv:1808.01560.

[16] Nagesh, P. Combination of facebook prophet and attention-based LSTM with multi-source data for Indian stock market prediction. Dissertation. Dublin. 2021 Technological University Dublin. doi:10.21427/ tszy-4r42

[17] Jiang, Xinxin & Pan, Shirui & Jiang, Jing & Long, Guodong. (2018). Cross-Domain Deep Learning Approach For Multiple Financial Market Prediction. 1-8. 10.1109/IJCNN.2018.8489360.

[18] Deng, Y., Bao, F., Kong, Y., Ren, Z., & Dai, Q. "Deep direct reinforcement learning for financial signal representation and trading". 2021 IEEE Transactions on Neural Networks and Learning Systems, p.p 653–664.

[19] Almahdi, S., & Yang, S. Y. "An adaptive portfolio trading system: A risk-return portfolio optimization using recurrent reinforcement learning with expected maximum drawdown. Expert Systems with Applications", 2017, p,p 267–279.

[20] Zeng, Z.; Khushi, M. "Wavelet denoising and attention-based RNN- ARIMA model to predict forex price". In Proceedings of the 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, UK, July 2020, p.p 19–24.

[21] Y. Wang and Y. Guo, "Forecasting method of stock market volatility in time series data based on mixed model of ARIMA and XGBoost," in China Communications, vol. 17, no. 3, pp. 205-221, March 2020, doi: 10.23919/JCC.2020.03.017.

[22] Y. Du, "Application and analysis of forecasting stock price index based on combination of ARIMA model and BP neural network," 2018 Chinese Control And Decision Conference (CCDC), Shenyang, China, 2018, pp. 2854-2857, doi: 10.1109/CCDC.2018.8407611.

[23] Krausa, M., & Feuerriegel, S." Decision support from financial disclosures with deep neural networks and transfer learning" Zurich, Germany.

[24] Rana, Masud & Uddin, Mohsin & Hoque, Md. (2019). Effects of Activation Functions and Optimizers on Stock Price Prediction using LSTM Recurrent Networks. 354-358. 10.1145/3374587.3374622.

[25] Xiaodong Li, Wenpeng Wang, "Incorporating stock prices and news sentiments for stock market prediction: A case of Hong Kong", in Information Processing & Management, Volume 57, 2020.

[26] S. Selvin, R. Vinayakumar, E. A. Gopalakrishnan, V. K. Menon and K. P. Soman, "Stock price prediction using LSTM, RNN and CNN-sliding window model,"" in International Conference on Advances in Computing, Communications and Informatics, Udupi, India, 2017, pp. 1643-1647.

[27] R. Uddin, F. I. Alam, A. Das and S. Sharmin, "Multi-Variate Regression Analysis for Stock Market price prediction using Stacked LSTM," in International Conference on Innovations in Science, Engineering and Technology, Chittagong, Bangladesh, pp. 474-479, 2022.

[28] K. Saleh, M. Hossny and S. Nahavandi, "Intent prediction of vulnerable road users from motion trajectories using stacked LSTM network," 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), Yokohama, Japan, 2017, pp. 327-332, doi: 10.1109/ITSC.2017.8317941.

[29] Skehin, T.; Crane, M.; Bezbradica, M. Day ahead forecasting of FAANG stocks using ARIMA, LSTM networks and wavelets. In Proceedings of the 26th AIAI Irish Conference on Artificial Intelligence and Cognitive Science, Dublin, Ireland, 6–7 December 2018.

[30] Lai, C.Y.; Chen, R.-C.; Caraka, R.E. Prediction stock price based on different index factors using LSTM. In Proceedings of the 2019 International Conference on Machine Learning and Cybernetics (ICMLC), Kobe, Japan, 7–10 July 2019.

[31] A. H. Bukhari, M. A. Z. Raja, M. Sulaiman, S. Islam, M. Shoaib and P. Kumam, "Fractional Neuro- Sequential ARFIMA-LSTM for Financial Market Forecasting," in IEEE Access, vol. 8, pp. 71326-71338, 2020, doi: 10.1109/ACCESS.2020.2985763.

[32] Y. Weng, X. Wang, J. Hua, H. Wang, M. Kang and F. -Y. Wang, "Forecasting Horticultural Products Price Using ARIMA Model and Neural Network Based on a Large-Scale Data Set Collected by Web Crawler," in IEEE Transactions on Computational Social Systems, vol. 6, no. 3, pp. 547-553, June 2019, doi: 10.1109/TCSS.2019.2914499.

[33] C. Li, X. Zhang, M. Qaosar, S. Ahmed, K. M. R. Alam and Y. Morimoto, "Multi-factor Based Stock Price Prediction Using Hybrid Neural Networks with Attention Mechanism," *IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology congress*, Fukuoka, Japan, 2019, pp. 961-966.

[34] Arslan S. A hybrid forecasting model using LSTM and Prophet for energy consumption with decomposition of time series data. PeerJ Comput Sci. 2022. doi: 10.7717/peerj-cs.1001.

[35] K. Chen and F. Dai, "A LSTM-based method for stock returns prediction: A case study of China stock market", in IEEE International Conference on Big Data (Big Data), Santa Clara, CA, USA, 2015, pp. 2823-2824.

[36] C. Saiktishna, N. S. V. Sumanth, M. M. S. Rao and T. J, "Historical Analysis and Time Series Forecasting of Stock Market using FB Prophet," in 6th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2022, pp. 1846-1851.

[37] M. G. Sousa, K. Sakiyama, L. d. S. Rodrigues, P. H. Moraes, E. R. Fernandes and E. T. Matsubara, "BERT for Stock Market Sentiment Analysis," in IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI), Portland, OR, USA, 2019, pp. 1597-1