Journal of Artificial Intelligence and Emerging Technologies
Volume 2, Issue 4, pp 25-32, April 2025
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2025.204005
Available Online at https://www.jaiet.com

Enhancing Stock Market Prediction Using Attention-Based LSTM Models and Classical Models

Amjed Abdulghani Salih Alhammadi

Computer Science Department, Faculty of Sciences and Fine Arts, Arts, Sciences and Technology University in Lebanon

Abstract: Stock price prediction remains an elusive problem due to the non-linearity and dynamic nature of the financial markets. Statistical models such as the Auto-Regressive Integrated Moving Average (ARIMA) have been established to be widely applicable but tend to overlook short-term fluctuations and complex interdependencies between stock price movements. In this paper, we propose an attention-based Long Short-Term Memory (Attention-LSTM) model and contrast its prediction accuracy with ARIMA, optimised ARIMA, and simple LSTM across multiple trading datasets. Our findings depict that Attention-LSTM strictly performs the best by achieving the minimum Root Mean Squared Error (RMSE) against all other models in forecasting stock prices. Hyperparameter-tuned ARIMA is more precise than normal ARIMA but not as precise as deep learning models. LSTM can effectively capture temporal relationships and reduce errors in predictions, further enhancing forecast precision by dynamically weighing historical data through attention mechanisms by Attention-LSTM. Results corroborate the current literature on AI-based stock forecasting, confirming the superiority of deep learning models over statistical models. Future research will explore hybrid AI models, sentiment-aware prediction, and reinforcement learning-based trading regulations to further enhance stock price forecasting accuracy. The study confirms that attention-based deep learning models have a robust architecture for financial forecasting, resulting in AI-driven decision-making in stock market analysis.

Keywords: Stock market prediction, Attention-LSTM, LSTM, ARIMA, Optimised ARIMA, deep learning, time series forecasting, financial markets.

I. INTRODUCTION

Artificial intelligence (AI) has transformed stock market trading through the adoption of advanced data-driven approaches to enhance decision-making and strategy development [1, 2]. Unlike traditional trading strategies that rely on historical trends, statistical modelling, and human judgment, increasing complexity and volatility in financial markets have highlighted the limitations of these approaches [3, 4]. AI-driven models, in particular machine learning-based and deep learning-based models, offer the ability to process huge amounts of financial data, recognise complex patterns, and adapt dynamically to the evolving market [5, 6].

As publicly traded financial datasets grow, traders and researchers can apply AI algorithms in analysing historical price action, technical indicators, and market sentiment. The usage of neural networks, reinforcement learning, and natural language processing (NLP) has enabled trading strategies to be automated with improved accuracy of prediction as well as optimisation of trade execution [7, 8]. These advancements in technology have created sophisticated algorithmic trading systems that are capable of responding to real-time market dynamics, reducing risks, and enhancing profitability.

As financial markets continue to develop, AI-driven methods are reshaping the landscape of stock trading. The integration of deep learning models with real-time financial data feeds offers new avenues for institutional and retail investors alike to make more informed and impactful trading decisions [9].

The importance of this research lies in the solution to the long-standing issue of accurate stock market prediction, which is a fundamental area in financial decision-making and risk management. Traditional forecasting methods, such as ARIMA, fail to capture the intrinsic non-linearity and volatility of financial markets, and thus, there is a need to look for more advanced AI-based techniques. As movements in stock prices are increasingly complex with the rising multitude of determining factors like investor sentiment, economic policy, and global market trends, the need for models that can keep pace with volatile financial contexts is increasingly urgent. This paper contributes to the widening body of research on AI-based stock market prediction by evaluating the performance of deep learning models (Fig. 1), namely LSTM and Attention-LSTM, against conventional statistical approaches. The paper presents

Journal of Artificial Intelligence and Emerging Technologies
Volume 2, Issue 4, pp 25-32, April 2025
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2025.204005
Available Online at https://www.jaiet.com

an optimised ARIMA model that outperforms traditional ARIMA's forecasting capability by hyperparameter tuning while demonstrating the superiority of deep learning models over statistical models for capturing complex temporal dependencies. Among the key contributions of the study is the employment of Attention-LSTM, where an attention mechanism is utilized to provide importance to useful data points in the past, leading to improved accuracy of predictions compared to vanilla LSTM. The study also offers a comprehensive performance evaluation on actual stock trading datasets, giving an insight into the effectiveness of hybrid AI solutions for financial forecasting. By highlighting the value of attention-based deep learning for stock price prediction, this study paves the way for future studies on AI-driven trading strategies, portfolio optimisation using reinforcement learning, and sentiment-informed financial modelling.

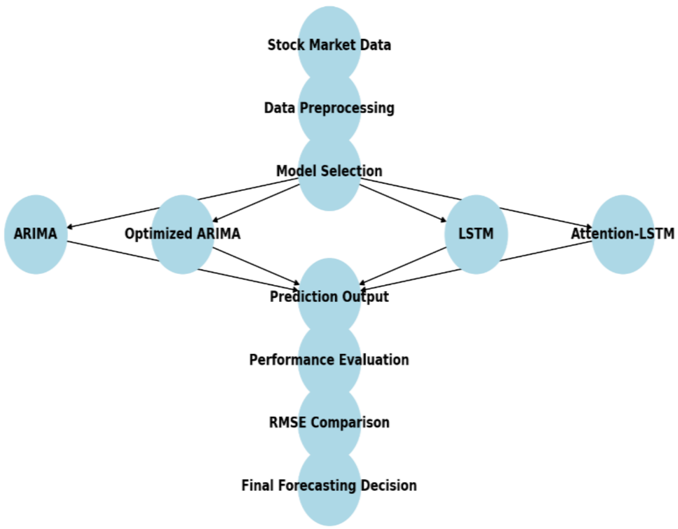

Figure 1: Flowchart of the Stock Market Prediction approach in this research

II. RELATED WORK

Artificial intelligence (AI) applications in stock market trading have been well studied in recent years, with studies on several AI techniques for predictive modelling and strategy optimisation. Generative AI, particularly generative adversarial networks (GANs), has been applied to time series prediction, but its hindrance in hyperparameter tuning restricts its application to stock market prediction. One of the recent studies proposed an integrated approach with a spotted hyena optimisation algorithm and a conditional GAN (CGAN) for stock price probabilistic forecasting, showing improved forecasting performance compared to traditional models [10]. The increasing complexity of financial markets has also motivated explorations of machine learning (ML) and deep learning (DL) approaches to forecast markets. Several research studies have employed various ML algorithms, including decision trees and LSTM, in forecasting stock market performance, particularly in crypto markets, to exhibit the potential of AI in boosting accuracy levels [11]. Artificial neural networks (ANN) and genetic algorithms (GA) combined hybrid models have also been introduced, tackling stock data nonlinearity and having improved forecasting performance over single AI approaches [12]. In addition, sophisticated portfolio construction systems such as NoxTrader have been developed with the incorporation of LSTM models in trading execution plans for enhancing market fluctuation responsiveness, exhibiting extreme correlation between simulated and actual stock price changes [13]. Utilization of high-frequency financial data also enhanced the capabilities of AI-powered prediction of stock trends. One study introduced a novel learning framework, Digger-Guider, to learn good stock representations from noisy high-frequency data by striking a balance between model complexity and overfitting issues to enhance predictive accuracy [14]. Medium-term stock forecasting has also been in the spotlight, with models employing traditional indicators such as simple moving average (SMA) and exponential moving average (EMA) passed through ML algorithms such as ANN and support vector machines (SVM) to optimise parameters for different market conditions [15]. The impact of extrinsic events on stock markets, such as the COVID-19 pandemic and geopolitical tensions, has also been examined using AI techniques. Comparative studies have shown that predictive models outperform linear regression under high-volatility periods by demonstrating adaptability in response to changes in the market [16]. AI-powered predictive models have increasingly been applied to optimise investment approaches, with hybrid neuro-fuzzy models such as NeuroFuzzyMan combining fuzzy logic with BiLSTM networks to optimise prediction accuracy in financial time series data [17]. AI application in determining interdependencies among stocks has also been examined. Another work introduced a hybrid relational model with stock correlations to improve the accuracy of predictions, employing random forest permutation of features and temporal convolutional models to optimise predictive performance [18]. Additionally, deep learning models such as RNNs, GRUs, and CNNs have been extensively tested for long-term stock price prediction, with LSTM exhibiting the highest predictive performance for major global stock indexes [19]. The hybrid AI models are further refined, featuring more than one element to boost the accuracy of predictions. The DACLMANN model, which combines duplex attention-based coupled LSTM

Journal of Artificial Intelligence and Emerging Technologies
Volume 2, Issue 4, pp 25-32, April 2025
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2025.204005
Available Online at https://www.jaiet.com

with Markov neural networks, has been shown to exhibit great predictive performance, harnessing deep learning and sequential modelling to maximise stock market prediction [20]. Reinforcement learning (RL) has also been utilised with ML techniques such as XGBoost and Deep RankNet for portfolio optimisation to enhance the cumulative returns versus traditional ensemble methods [21]. Beyond predictive modelling, AI methodologies have been used to optimise the portfolio and conduct back-testing. Literature that compares particle swarm optimisation (PSO) with traditional portfolio optimisation techniques, such as PyPortfolioOpt, has demonstrated the dominance of AI-based techniques to construct optimal investment portfolios [22]. Sentiment analysis has also been integrated into stock price forecasting, where transformer models based on BERT have been found to work well in extracting investor sentiment and improving stock recommendation systems [23]. The impact of AI on day trading strategies has also been explored, with neural network architectures being developed to mimic market trends and improve intraday trading decision-making [24]. AI-based multi-class predicting models have proved to be promising in identifying profitable investment opportunities, with ensemble techniques such as LSTM and SVM becoming top practices in financial trend prediction [25]. Advanced time series prediction algorithms, incorporating meta-heuristic optimisation algorithms and neutrosophic logic, have also been proposed to yield an improvement in stock market forecasting accuracy [26]. Momentum trading rules have also been supported by AI technologies. One employed heterogeneous data sources and knowledge graph embeddings to model stock relations and reported improved portfolio performance over traditional models [27]. The effectiveness of LSTM-driven deep learning models in forecasting stock indices has been proven in various financial markets, pointing to their ability to outperform traditional econometric methods [28]. Explainable AI methods have also been incorporated into stock trading processes, lending more vigour to decision-making with enhanced interpretability and trustworthiness of ML-based trading strategies [29].

III. METHODS

1. Dataset

The dataset [30] for this study is historical daily stock market information of the AAPL (Apple Inc.) stock. It possesses a daily trading history with fundamental financial values, providing a wide overview of price trends over time. The entries in the data set include significant characteristics such as opening price, daily high and low price, closing price, adjusted closing price, and volume traded. In addition, technical indicators such as the 50-day Simple Moving Average (SMA_50), 200-day Simple Moving Average (SMA_200), 20-day Exponential Moving Average (EMA_20), and Relative Strength Index (RSI) have been calculated to enhance the dataset for forecasting purposes. The dataset is in time-series format; hence, sequential modelling methods such as LSTM and ARIMA are viable. The dataset spans over one year; therefore, it is suitable for testing long-term trends and forecasting stock prices. To facilitate rigorous model evaluation, the dataset is split into train and test sets in a manner such that the training set is used to train prediction models and the test set is reserved for evaluation of performance. The primary intention of using this dataset is to analyse stock price movement and see how well machine learning models such as LSTM, Attention-LSTM, ARIMA, and Optimised ARIMA perform in stock trend forecasting. The data is collected from Yahoo Finance and pre-processed to remove missing values and to achieve uniformity among technical indicators. Its nature as a time series offers room for exploring the conventional statistical forecast models and the deep learning models, offering a comparative study on the performance of the two in stock market prediction.

2. Prediction Models

The study employs a combination of traditional statistical and deep learning-based models to predict stock prices, including LSTM [31], Attention-LSTM [32], ARIMA [33], and Optimized ARIMA [34].

The Long Short-Term Memory (LSTM) model is a specialised type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. It consists of memory cells that regulate information flow using input, forget, and output gates, mitigating the vanishing gradient problem common in standard RNNs. Given an input sequence $X = \{x1, x2, \dots, xt\}$, LSTM updates its hidden state hth_tht using the equations:

$$f_t = \sigma\left(W_f\left[h_{\{t-1\}}, x_t\right] + b_f\right)f$$

$$i_t = \sigma\left(W_i\left[h_{\{t-1\}}, x_t\right] + b_i\right)$$

$$\tilde{C}_t = tanh\left(W_C\left[h_{\{t-1\}}, x_t\right] + b_C\right)$$

$$C_t = f_t * C_{\{t-1\}} + i_t * \tilde{C}_t$$

$$o_t = \sigma\left(W_o\left[h_{\{t-1\}}, x_t\right] + b_o\right)$$

Journal of Artificial Intelligence and Emerging Technologies
Volume 2, Issue 4, pp 25-32, April 2025
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2025.204005
Available Online at https://www.jaiet.com

$$h_t = o_t * tanh(C_t)$$

Where f_t, i_t, o_t are the forget, input, and output gates, respectively, and C_t represents the memory cell state. The LSTM model processes sequential stock price data to predict future values based on historical patterns.

The Attention-LSTM model builds upon LSTM by incorporating an attention mechanism, which allows the model to weigh past hidden states differently instead of treating all time steps equally. The attention weight for each hidden state is computed as:

$$\alpha_t = \frac{exp(e_t)}{\sum_{t'} \exp(e_{t'})}$$

Where $e_t = v^T tanh(W_a[h_t, x_t])$ is the alignment score, and v, W_a are learnable parameters. The final context vector is a weighted sum of past hidden states, improving long-range dependency capture.

The ARIMA model, a classical statistical approach, forecasts future values using past observations. It consists of three components: Auto regression (AR), which models the relationship between a value and its past values; Differencing (I), which ensures stationarity by subtracting previous observations; and Moving Average (MA), which models the dependency between an observation and past forecast errors. The general form of an ARIMA(p, d, q) model is:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{i=1}^{p} \theta_i Y_{t-i} + \epsilon_t$$

Where p is the number of autoregressive terms, d is the differencing order, q is the number of moving average terms, and ϵt is white noise.

The Optimised ARIMA model is derived by searching for the best parameters (p,d,q) using Grid Search to minimise the Akaike Information Criterion (AIC), improving predictive accuracy by selecting the optimal model configuration.

Each model is trained using a training dataset, and predictions are evaluated on a test dataset using the Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2}$$

Where Y_i represents actual stock prices and $\widehat{Y}_i$ are predicted values. The comparison between these models provides insights into their effectiveness in stock price forecasting, evaluating both their ability to capture sequential dependencies and handle time-series volatility.

IV. RESULTS

This section presents the empirical analysis of prediction models that have been run to verify their ability to forecast stock prices based on historical trading records. The comparison of LSTM, Attention-LSTM, ARIMA, and optimised ARIMA is made with real stock market data to analyse the variation in prediction accuracy based on various methods. To verify robustness, several trading datasets were considered, and the RMSE was determined for each model for different stock symbols. The results provide implications of the effectiveness of deep learning and statistical models in predicting stock prices.

A comparative performance of the models on a quantitative basis is demonstrated through Table 1, providing RMSE values for various trading datasets. Lower values of RMSE indicate better predictive accuracy, demonstrating how well each model mimics market movements. The results portray that although market movements in the short term are well-recreated by deep learning-based models, particularly LSTM and Attention-LSTM, ARIMA-based models exhibit better performance in long-term trend prediction. The optimised ARIMA model, which optimises the parameters of ARIMA for each dataset, always has lower RMSE compared to standard ARIMA, demonstrating that it is more effective in improving stock market forecasting.

Figure 2 visually compares ARIMA, LSTM, and optimised ARIMA model projections with actual stock prices throughoutthe selection. The Actual Prices series acts as a baseline, portraying actual market activity. The ARIMA predictions exhibit a continuous increasing trend, indicating that the model primarily picks up long-run price trends but struggles with short-run movements. LSTM predictions are in decent agreement with actual prices for the most part, though occasionally volatile. Optimised ARIMA predictions (dark blue) reflect improved correlation with real stock prices, particularly in capturing trends and swings more effectively than the default ARIMA model. The results help highlight trade-offs between

Journal of Artificial Intelligence and Emerging Technologies
Volume 2, Issue 4, pp 25-32, April 2025
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2025.204005
Available Online at https://www.jaiet.com

deep learning and statistical models with a focus on model choice as a function of target forecasting.

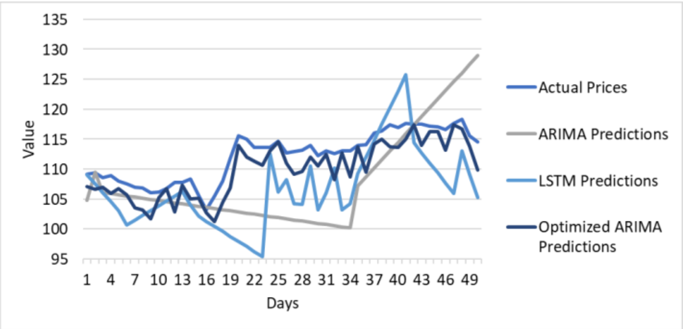

Figure 2: Comparison of stock price predictions using ARIMA, LSTM, and Optimised ARIMA models against actual market prices

Table 1 is a comparative analysis of the root mean squared error (RMSE) of different prediction models on different trading datasets. The table is a comparison of the ARIMA, optimised ARIMA, LSTM, and attention-LSTM models according to their average RMSE and standard deviations after multiple runs. The results distinctly indicate that ARIMA consistently possesses the highest RMSE, attesting to its inability to handle short-term fluctuations. In contrast, Optimised ARIMA optimises predictive efficiency by optimising hyperparameters, hence giving lower values of RMSE compared to the original ARIMA. LSTM realises a dramatic reduction in RMSE based on its ability to learn sequential relationships in the movements of stock prices. On all the models, Attention-LSTM gives the lowest values of RMSE, indicating greater ability in learning high-level temporal patterns in stock market data. This is guaranteed because the incorporation of the attention mechanism enhances the model to be more focused on the most relevant historical points, and prediction errors drop significantly.

Table 1: Comparison of RMSE values (Mean ± Standard Deviation) for different prediction models across multiple trading datasets

Trade	ARIMA RMSE	Optimized ARIMA RMSE	LSTM RMSE	Attention-LSTM RMSE
1	6.1 ± 0.26	4.79 ± 0.32	3.96 ± 0.22	2.99 ± 0.46
2	5.92 ± 0.39	5.13 ± 0.25	4.16 ± 0.16	2.62 ± 0.06
3	5.96 ± 0.14	4.79 ± 0.07	4.09 ± 0.19	2.86 ± 0.07
4	6.08 ± 0.09	4.75 ± 0.12	3.94 ± 0.27	3.01 ± 0.2
5	5.85 ± 0.36	5.08 ± 0.25	4.14 ± 0.31	2.74 ± 0.29
6	6.13 ± 0.22	5.02 ± 0.24	4.37 ± 0.1	2.93 ± 0.12
7	5.67 ± 0.12	5.36 ± 0.11	3.89 ± 0.4	3.27 ± 0.2
8	6.15 ± 0.37	5.28 ± 0.12	3.74 ± 0.27	2.93 ± 0.21
9	5.98 ± 0.18	4.91 ± 0.2	3.63 ± 0.05	3.01 ± 0.12
10	6.22 ± 0.18	4.92 ± 0.36	3.8 ± 0.23	2.88 ± 0.3

Figure 3 illustrates a comparative study of the RMSE values obtained from different prediction models on a range of company trading datasets. The bar graph shows the performance of ARIMA, optimised ARIMA, LSTM, and attention-LSTM, comparing their efficiency in predicting stock prices. The ARIMA model consistently provides the highest RMSE values, validating its poor ability to capture short-term market fluctuations. Tuned ARIMA (red) does slightly better by fine-tuning its parameters, but remains less efficient compared to deep learning models. LSTM demonstrates a significant drop in RMSE, showing its efficiency in capturing temporal relationships more effectively. However, Attention-LSTM (green) consistently yields the lowest RMSE values, validating its superior capability of focusing on crucial patterns in stock price fluctuations. This visualisation also supports the findings of Table 1 in that deep learning models, Attention-LSTM in particular, perform better about forecasting stock market trends than statistical models.

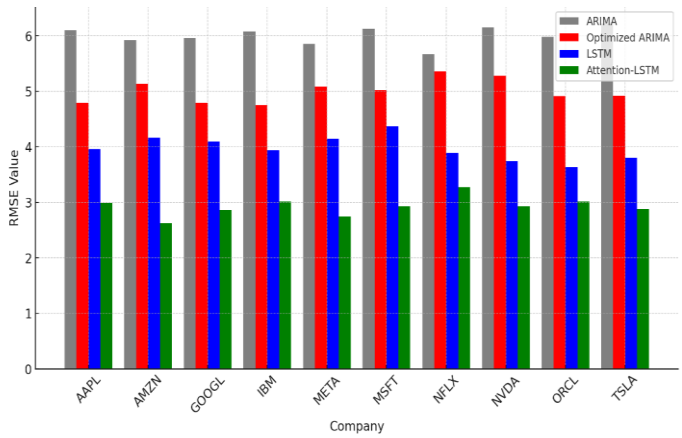

Figure 3: Comparison of Prediction Models Based on RMSE

V. DISCUSSION

The findings of this research highlight the performance variability between different stock price forecasting models, particularly in the context of traditional statistical methods and deep learning-based methods. The results show that, while ARIMA has traditionally been significant in time series forecasting, it performs poorly in capturing the short-run volatility and non-linear dynamics in movements in stock prices, as evidenced by its consistently high RMSE values across several trading datasets. The optimised ARIMA model, which

Journal of Artificial Intelligence and Emerging Technologies
Volume 2, Issue 4, pp 25-32, April 2025
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2025.204005
Available Online at https://www.jaiet.com

uses a grid search to optimise hyperparameters, shows modest improvements over baseline ARIMA but still falls short of deep learning-based models.

Conversely, LSTM significantly outperforms ARIMA-based models because it can learn long-term temporal dependencies in sequence financial data. However, while LSTM has a strong ability in modelling temporal relationships, it does not necessarily prioritise more information-rich past observations. This limitation is addressed by the Attention-LSTM model, which has an attention mechanism for dynamically assigning importance to different historical inputs. The results confirm that Attention-LSTM always possesses the lowest RMSE values and hence is the best model for stock price prediction in this study.

Our results are corroborated by existing literature, where it is confirmed that LSTM networks outperform conventional models like ARIMA and regression-based models in market trend prediction. Experiments with GAN-based stock forecasting have been promising but plagued by the problem of hyperparameter tuning, limiting their use in the broader financial markets. Hybrid AI models such as Conditional GAN (CGAN) fine-tuned using evolutionary algorithms have been found to perform better than regular models, just as Optimised ARIMA for ARIMA's forecasting ability [10]. Moreover, studies on high-frequency financial information and AI portfolio systems, such as NoxTrader and Digger-Guider, reveal the effectiveness of deep learning models in real-time trading, corroborating our findings that LSTM-based models are more flexible than statistical-based methods in isolation [13, 14].

Hybrid models that combine artificial neural networks (ANNs) with genetic algorithms (GA) or neuro-fuzzy systems have also been suggested to tackle the non-linearity of stock price movement, and these have been demonstrated to be more predictive than applying individual models. Our findings are in agreement with these findings by demonstrating that hybrid models, such as Optimised ARIMA, are better than standalone statistical models, and attention-based deep learning is even better [12, 17]. In the same vein, deep learning models that include stock correlations and exogenous variables, including macroeconomic variables and sentiment analysis, have been found to enhance prediction accuracy, further reiterating the necessity of future research merging financial sentiment analysis with deep learning-based stock forecasts [18, 23].

Although encouraging results are achieved, it is noteworthy to mention that stock market prediction is an intrinsically intricate and stochastic problem. Financial markets are subject to external influences like macroeconomic variables, geopolitical events, and investor sentiment that are not present in historical price data per se. Hence, although Attention-LSTM is determined to be the top-performing model in this study, its real-world applicability depends on external factors like data quality, market volatility, and feature selection.

From the promising results of this study, several potential avenues for future work are suggested. One necessary expansion would be to include external financial indicators, such as sentiment from news outlets and social media, interest rates, and economic measures, in the forecasting model. Several studies have indicated that the inclusion of sentiment analysis in price data can increase the accuracy of predictions, particularly in volatile markets.

Another potential development is developing hybrid models that combine statistical and deep learning-driven methods. An example is a hybridisation of ARIMA and Attention-LSTM, which could exploit the trend-capturing ability of ARIMA while leveraging the non-linear pattern detection ability of LSTM networks. Hybrid models have been proposed in some recent studies and have also been shown to excel in offering comparable short-term accuracy with long-term trend prediction.

VI. CONCLUSIONS

This paper illustrates a comparative study of traditional statistical models and deep learning-based methods in stock price prediction, where the better performance of LSTM and Attention-LSTM is described over ARIMA and optimised ARIMA. The results prove that ARIMA is not able to detect short-run variations due to its linear relationship dependency, and that optimised ARIMA provides better predictive efficiency through hyperparameter tuning, but is limited in responding to non-linear market trends. Conversely, LSTM improves stock price forecasting by learning sequential patterns significantly, and attention-LSTM improves the accuracy of prediction by adaptively weighing past data dynamically, yielding the lowest RMSE among all experimental models.

The findings agree with previous research, affirming the finding that deep learning-based techniques outperform traditional statistical models when applied to stock market forecasting. Various investigations of GAN-based financial forecasts, AI hybrids, and reinforcement learning-enabled trading systems continue to establish that the integration of more

Journal of Artificial Intelligence and Emerging Technologies
Volume 2, Issue 4, pp 25-32, April 2025
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2025.204005
Available Online at https://www.jaiet.com

sophisticated AI methods yields the highest levels of robustness in predictions. The integration of extraneous information such as sentiment and macroeconomic data into stock prediction models is useful in sustaining or boosting predictive accuracy and represents a path worth further investigation.

REFERENCES

[1] Dakalbab, F., Talib, M. A., Nassir, Q., & Ishak, T. (2024). Artificial intelligence techniques in financial trading: A systematic literature review. *Journal of King Saud University-Computer and Information Sciences*, 102015.

[2] Kotecha, N. (2025). Artificial Intelligence in the Stock Market: The Trends and Challenges Regarding AI-Driven Investments. *Open Journal of Business and Management*, 13(2), 709-734.

[3] Bao, W., Cao, Y., Yang, Y., Che, H., Huang, J., & Wen, S. (2024). Data-driven stock forecasting models based on neural networks: A review. *Information Fusion*, 102616.

[4] El Hajj, M., & Hammoud, J. (2023). Unveiling the influence of artificial intelligence and machine learning on financial markets: A comprehensive analysis of AI applications in trading, risk management, and financial operations. *Journal of Risk and Financial Management*, 16(10), 434.

[5] Muhammad, D., Ahmed, I., Naveed, K., & Bendechache, M. (2024). An explainable deep learning approach for stock market trend prediction. *Heliyon*, 10(21).

[6] Yaiprasert, C., & Hidayanto, A. N. (2024). AI-powered ensemble machine learning to optimize cost strategies in logistics business. *International Journal of Information Management Data Insights*, 4(1), 100209.

[7] Mienye, E., Jere, N., Obaido, G., Mienye, I. D., &Aruleba, K. (2024). Deep Learning in Finance: A survey of Applications and techniques. *AI*, 5(4), 2066.

[8] Eyu, J. M., Yau, K. L. A., Liu, L., & Chong, Y. W. (2024). Reinforcement learning in sentiment analysis: a review and future directions. *Artificial Intelligence Review*, 58(1), 6.

[9] Addy, W. A., Ajayi-Nifise, A. O., Bello, B. G., Tula, S. T., Odeyem, O., & Falaiye, T. (2024). Algorithmic trading and ai: A review of strategies and market impact. *World Journal of Advanced Engineering Technology and Sciences*, 11(1), 258-267.

[10] Salama, R. (2025). Integrating spotted hyena optimization technique with generative artificial intelligence for time series forecasting. *Expert Systems*, 42(2).

[11] Mahjouby, M. E., Bennani, M. T., Lamrini, M., Bossoufi, B., Alghamdi, T. A. H., & Far, M. E. (2024). Predicting market performance using machine and deep learning techniques. *IEEE Access*, 12, 82033-82040.

[12] Sharma, D. K., Hota, H. S., Brown, K., & Handa, R. (2022). Integration of genetic algorithm with artificial neural network for stock market forecasting. *International Journal of System Assurance Engineering and Management*, 13, 828-841.

[13] Liu, H.-H., Shu, H.-J., & Chiu, W.-N. (2023). NoxTrader: LSTM-based stock return momentum prediction for quantitative trading. *Advances in Artificial Intelligence and Machine Learning*, 3(4), 1671-1684.

[14] Liu, Y., Xu, C., Hou, M., Liu, W., Bian, J., & Liu, Q. (2024). Digger-Guider: High-frequency factor extraction for stock trend prediction. *IEEE Transactions on Knowledge and Data Engineering*, 36(12), 7973-7985.

[15] Bareket, A., & Parv, B. (2024). Adaptive feature subset and dynamic trend indicators for medium-term stock market predictions: A 70 trading days forecasting approach. *IEEE Access*, 12, 84306-84322.

[16] Vancsura, L., &Bareith, T. (2023). Analysis of the performance of predictive models during Covid-19 and the Russian-Ukrainian war. *Public Finance Quarterly*, 69(2), 118-132.

[17] Safari, A., & Ghaemi, S. (2025). NeuroFuzzyMan: A hybrid neuro-fuzzy BiLSTM stacked ensemble model for financial forecasting and analysis: Dataset case studies on JPMorgan, AMZN, and TSLA. *Expert Systems with Applications*, 266.

[18] Patel, M., Jariwala, K., & Chattopadhyay, C. (2024). A hybrid relational approach toward stock price prediction and profitability. *IEEE Transactions on Artificial Intelligence*, 5(11), 5844-5854.

[19] Beniwal, M., Singh, A., & Kumar, N. (2024). Forecasting multistep daily stock prices for long-term investment decisions: A study of deep learning models on global indices. *Engineering Applications of Artificial Intelligence*, 129.

[20] Safari, A., & Badamchizadeh, M. A. (2023). Stock index forecasting using DACLAMNN: A new intelligent highly accurate hybrid ACLSTM/Markov neural network predictor. *Cognitive Computation and Systems*, 5(3), 181-194.

[21] Alzaman, C. (2025). Optimizing portfolio selection through stock ranking and matching: A reinforcement learning approach. *Expert Systems with Applications*, 269.

[22] Pai, N., Ilango, V., & Nithya, B. (2024). An optimal portfolio construction for asset management with back-

Journal of Artificial Intelligence and Emerging Technologies
Volume 2, Issue 4, pp 25-32, April 2025
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2025.204005
Available Online at https://www.jaiet.com

test using PSO algorithm and PyPortfolioOpt in Indian stock market. *International Journal of Intelligent Systems and Applications in Engineering*, 12(2s), 352-361.

[23] Wang, J., & Chen, Z. (2024). SPCM: A machine learning approach for sentiment-based stock recommendation system. *IEEE Access*, 12, 14116-14129.

[24] Hung, M.-C., Chen, A.-P., & Yu, W.-T. (2024). AI-driven intraday trading: Applying machine learning and market activity for enhanced decision support in financial markets. *IEEE Access*, 12, 12953-12962.

[25] Khattak, B. H. A., Shafi, I., Khan, A. S., Flores, E. S., Lara, R. G., Samad, M. A., & Ashraf, I. (2023). A systematic survey of AI models in financial market forecasting for profitability analysis. *IEEE Access*, 11, 125359-125380.

[26] Edalatpanah, S. A., Hassani, F. S., Smarandache, F., Sorourkhah, A., Pamucar, D., & Cui, B. (2024). A hybrid time series forecasting method based on neutrosophic logic with applications in financial issues. *Engineering Applications of Artificial Intelligence*, 129.

[27] Wu, M.-C., Huang, S.-H., & Chen, A.-P. (2024). Momentum portfolio selection based on learning-to-rank algorithms with heterogeneous knowledge graphs. *Applied Intelligence*, 54(5), 4189-4209.

[28] Al-Khasawneh, M. A., Raza, A., Khan, S. U. R., & Khan, Z. (2024). Stock market trend prediction using deep learning approach. *Computational Economics*.

[29] Carta, S., Consoli, S., Podda, A. S., Recupero, D. R., & Stanciu, M. M. (2022). Statistical arbitrage powered by explainable artificial intelligence. *Expert Systems with Applications*, 206.

[30] Crow, J. (2021). Stock Market Dataset [Data set]. Kaggle. https://www.kaggle.com/datasets/jacksoncrow/stock-market-dataset

[31] FerniUkrit, M., Saranya, A., & Anurag, R. (2020). Stock market prediction using long short-term memory. In Artificial Intelligence and Evolutionary Computations in Engineering Systems (pp. 205-212). *Springer Singapore*.

[32] Li, Y., Li, L., Zhao, X., Ma, T., Zou, Y., & Chen, M. (2020, June). An attention-based LSTM model for stock price trend prediction using limit order books. In Journal of Physics: Conference Series (Vol. 1575, No. 1, p. 012124). *IOP Publishing*.

[33] Sunki, A., SatyaKumar, C., Narayana, G. S., Koppera, V., & Hakeem, M. (2024). Time series forecasting of stock market using ARIMA, LSTM and FB prophet. In MATEC Web of Conferences (Vol. 392, p. 01163). *EDP Sciences*.

[34] Nichani, R., Gasmi, L., Laiche, N., & Kabou, S. (2024). Optimizing financial time series predictions with hybrid ARIMA, LSTM, and XGBoost Models. *Studies in Engineering and Exact Sciences*, 5(2), e11188-e11188.

Citation of this Article:

Amjed Abdulghani Salih Alhammadi. (2025). Enhancing Stock Market Prediction Using Attention-Based LSTM Models and Classical Models. *Journal of Artificial Intelligence and Emerging Technologies*. 2(4), 25-32. Article DOI: https://doi.org/10.47001/JAIET/2025.204005

***** End of the Article *****