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Performance Analysis of Quantum Long Short-Term Memory (QLSTM) Models for TLKM Stock Price Prediction

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Abstract−Stock price prediction is a challenging task due to its nonlinear, dynamic, and temporal characteristics, yet accurate forecasting models are crucial for decision-making in volatile stocks such as PT Telkom Indonesia Tbk (TLKM). Despite the rapid adoption of AI-based forecasting methods, several research gaps remain. Empirical studies on Quantum Long Short-Term Memory (QLSTM) are still relatively limited compared to classical LSTM variants, particularly for emerging market datasets. Existing research also tends to emphasize architectural comparisons rather than systematically analyzing training configurations. The joint effects of optimizer selection, epoch number, and hidden unit size on QLSTM performance have not been comprehensively evaluated, and many studies rely on limited evaluation metrics, reducing the strength of robustness assessment. To address these gaps, this study applies a QLSTM model to predict stock opening prices using historical time-series data and systematically evaluates the impact of different optimizers. The model is trained using Adam, Nadam, RMSprop, and SGD with epoch variations (50–250) and hidden units (8, 16, 32). Performance is measured using accuracy, MAE, MSE, RMSE, MAPE, and R^2 to ensure a comprehensive evaluation. The results indicate that adaptive optimizers consistently outperform SGD, with Adam providing the most stable and accurate predictions, highlighting the importance of optimizer choice and hyperparameter configuration in QLSTM-based stock forecasting.

Keywords: Share; Stocks; TLKM; Forecatsing; QLSTM

1. INTRODUCTION

The capital market plays a crucial role in fostering national economic growth by functioning as a long-term financial system that facilitates equity transactions, provides capital financing for corporations, and serves as an investment vehicle for the public. Within a market-based economic framework, the capital market contributes significantly to economic development by offering alternative financing mechanisms for listed companies, with stocks being among the most actively traded instruments representing ownership rights or equity participation by individual and institutional investors [1].

However, stock prices exhibit highly volatile behavior and tend to fluctuate continuously over time as a result of the interaction of multiple influencing factors. Price movements are primarily governed by market conditions, particularly the balance between supply and demand, where increased investor demand under limited share availability generally leads to price increases, while excess supply relative to demand results in price declines. Beyond these dynamics, stock prices are further shaped by various internal and external factors, including macroeconomic conditions, corporate financial performance, government policies, global economic developments, and market sentiment driven by investor behavior and perceptions, leading to highly complex price dynamics that make accurate prediction challenging without appropriate analytical and modeling approaches[2]. The high volatility of stock prices poses a significant challenge for investors in formulating optimal investment strategies.

PT Telkom Indonesia (Persero) Tbk (TLKM) is one of the largest publicly listed companies in Indonesia, with significant market capitalization on the Bursa Efek Indonesia, operating in the telecommunications and digital services sector. Supported by strong corporate performance and a solid reputation, TLKM shares attract substantial investor interest, driven by the company’s strategic role in national telecommunications infrastructure and the rapid growth of Indonesia’s digital ecosystem, which underpins its long-term business prospects [3]. Nevertheless, stock price movements remain highly dynamic and are influenced by multiple macroeconomic, political, and sentiment-related factors at both national and global levels, resulting in high uncertainty and volatility. This complexity limits the effectiveness of conventional analytical approaches, such as technical and fundamental analysis, in capturing non-linear patterns and rapidly evolving market dynamics, thereby making accurate stock price prediction a challenging task[4].

Stock price prediction is a complex problem due to the non-linear, stochastic nature of financial data and the influence of multiple interrelated factors. This complexity limits the effectiveness of conventional approaches, such as technical and fundamental analysis, in fully capturing price movement patterns. With advances in technology, artificial intelligence (AI) has been increasingly applied in financial analysis, particularly for stock price modeling and prediction[5]. AI-based approaches enable large-scale data processing, the identification of hidden patterns that are difficult to detect using traditional methods, and the generation of predictions that adapt more effectively to dynamic market conditions[6].

Among AI techniques for time-series modeling, Long Short-Term Memory (LSTM)[7] networks are widely used as an enhancement of Recurrent Neural Networks (RNNs)[8][9] to improve learning over long data sequences. Through its internal gating mechanisms, LSTM addresses the vanishing gradient problem commonly encountered in

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conventional RNNs, enabling more effective learning of long-term temporal dependencies [10]. Building upon this framework, Quantum Long Short-Term Memory (QLSTM) has been introduced as an advanced extension that integrates principles of quantum computing into time-series modeling. By leveraging quantum computational characteristics, QLSTM enables richer representations of complex and non-linear temporal patterns and is expected to enhance the model's capability to capture intricate time-series dynamics beyond those achievable with conventional LSTM approaches [11].

Quantum Long Short-Term Memory (QLSTM) is developed to enhance time-series modeling by integrating quantum computing principles into the Long Short-Term Memory architecture, enabling richer representations of non-linear patterns and long-term dependencies in dynamic stock price data[2]. However, QLSTM performance is strongly influenced not only by its architecture but also by key training parameters, including the number of epochs, hidden units, and optimization algorithms[12][13]. Inappropriate epoch selection may lead to underfitting or overfitting, while an unsuitable number of hidden units can limit the model's capacity or increase unnecessary complexity[14]. In addition, the choice of optimizer plays a critical role in weight updates, convergence speed, and training stability. Optimizers such as Stochastic Gradient Descent (SGD), Adam, RMSprop, and Nadam exhibit distinct characteristics in handling gradients and learning rates. The optimal combination of these parameters is expected to improve QLSTM performance, which is evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2 Score to assess the accuracy and robustness of TLKM stock price predictions[15][16][17].

Previous study investigated stock price prediction of PT Telkom Indonesia (Persero) Tbk using the LSTM algorithm by comparing several optimization techniques. Using TLKM stock data from January 2019 to January 2023 and focusing on opening prices, the study evaluated different epoch configurations (25, 50, 75, and 100) and optimizers (Adam, SGD, and RMSprop), with a 75:25 training–testing split. The results indicated that the Adam optimizer achieved the best performance, reaching an accuracy of 98.59% at 100 epochs, highlighting the significant influence of optimizer choice and training parameters on LSTM-based stock price prediction [7].

In a CNN–LSTM hybrid model was proposed to predict TLKM stock prices using a longer historical dataset and closing prices as the primary time-series variable. The model combined CNN for local feature extraction and LSTM for long-term temporal dependency learning. The evaluation considered variations in learning rate, kernel size, and epochs, with the optimal configuration achieving MAE of 56.13, RMSE of 75.75, and R^2 of 0.973, demonstrating improved predictive accuracy over a standalone LSTM and emphasizing the importance of architectural enhancement and hyperparameter tuning [16].

Further architectural exploration was conducted in other study, which compared LSTM and BiLSTM models for TLKM stock price prediction using daily closing price data from 2019 to 2023. By leveraging bidirectional temporal processing and optimizing parameters such as neuron units, batch size, epochs, and dropout via grid search, the BiLSTM model achieved a lower RMSE (0.0172) than LSTM (0.0199), indicating superior performance in capturing dynamic and bidirectional temporal patterns [18].

The application of QLSTM was first introduced in this study, where QLSTM and classical LSTM were compared for general time-series forecasting tasks. By replacing classical memory cells with variational quantum circuits (VQC), the study demonstrated that QLSTM achieved faster convergence and lower prediction errors on solar energy production datasets, with MAE and RMSE values significantly outperforming LSTM. These results suggest that QLSTM provides superior representational capability for complex non-linear temporal patterns, despite higher computational costs due to quantum simulation [11].

Similarly, implemented QLSTM using the PennyLane framework integrated with PyTorch to forecast non-linear rainfall time-series data from Seattle and Ukraine. Through Bayesian optimization of hyperparameters such as hidden units, qubits, and quantum layers, QLSTM consistently outperformed LSTM in terms of MAE, RMSE, and prediction stability across both datasets, reinforcing its effectiveness in modeling complex temporal dynamics [19].

Moreover, study proposed a hybrid Broad Learning System–QLSTM (BLS-QLSTM) model for stock index forecasting on multiple Chinese indices. By integrating phase space reconstruction, BLS, and QLSTM, the hybrid model consistently outperformed both LSTM and standalone QLSTM across multiple error metrics and directional accuracy, demonstrating that architectural enrichment combined with quantum-enhanced modeling can further improve forecasting performance [20].

Despite the growing application of artificial intelligence based models for stock price prediction, several research gaps remain evident. First, empirical studies on Quantum Long Short Term Memory QLSTM are still relatively limited compared to conventional LSTM or BiLSTM models, particularly in emerging markets such as Indonesia. Second, existing studies tend to emphasize architectural modifications or comparisons between classical and quantum inspired models, while the systematic investigation of training parameter configurations remains underexplored. In particular, the combined and interactive effects of critical hyperparameters such as the number of epochs, hidden units, and optimization algorithms have not been comprehensively analyzed. Third, there is a lack of structured evaluation that integrates multiple performance metrics to assess both prediction accuracy and model robustness within a unified experimental framework.

To address these gaps, this study aims to evaluate the performance of QLSTM in predicting the stock prices of PT Telkom Indonesia Persero Tbk TLKM by systematically examining the influence of different training parameter configurations, including epoch variations, optimizer selection using SGD, RMSprop, and Adam, as well as hidden

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unit sizes. Model performance is assessed using multiple evaluation metrics including MAE, MSE, RMSE, MAPE, and R^2 Score to provide a comprehensive and statistically grounded analysis of prediction accuracy and robustness.

2. RESEARCH METHODOLOGY

2.1 Research Flow

The flow of this research can be described with a flowchart as in Figure 1. Based on Figure 1, This study begins with a literature review to identify relevant methods for TLKM stock price prediction using the Quantum Long Short-Term Memory (QLSTM) model. Based on the review, a QLSTM-based prediction model is developed using historical opening price data of PT Telkom Indonesia Tbk (TLKM**)**. The model performance is evaluated by comparing several optimizers, namely Adam, Nadam, SGD, and RMSprop, as well as variations in training epochs and hidden units. Evaluation is conducted using standard regression metrics without incorporating external variables.

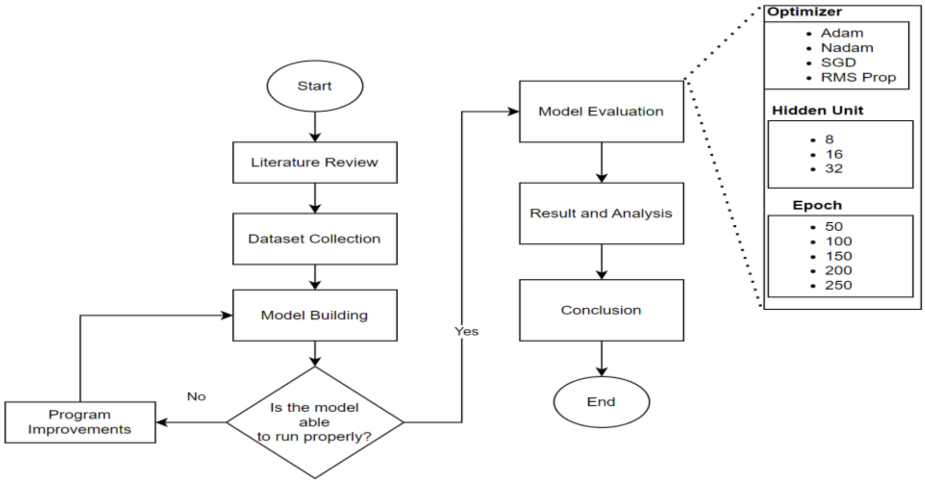

Figure 1. Research Flow

2.2 Model Design

Next, historical stock price data of PT Telkom Indonesia Tbk (TLKM) are collected, focusing on the opening price as the primary variable. The data are obtained from reliable public sources such as Yahoo Finance or Google Finance, covering the period from January 1, 2020, to January 1, 2026, then verified to remove duplicates, missing values, and anomalies before being prepared for preprocessing, normalization, and division into training and testing sets for QLSTM-based stock price prediction.

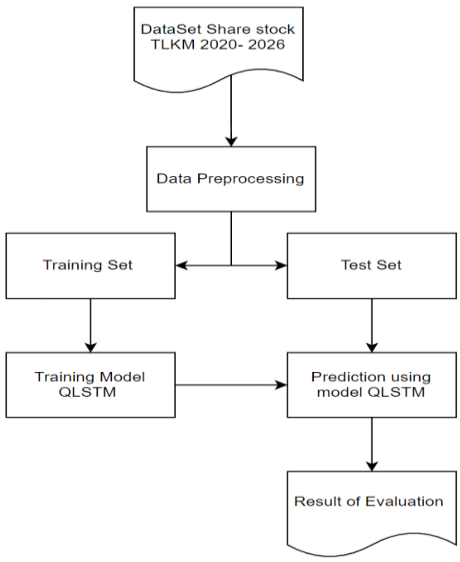

Figure 2. QLSTM Program Flow

Based on Figure 2, the model development begins by utilizing the TLKM stock dataset for the period 2020–2026 as the primary data source. The data are divided sequentially, without shuffling, into 80% for training and 20%

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for validation to preserve the chronological structure of the time series. This Time Series Split approach ensures that the model learns from past observations and is evaluated on future unseen data, thereby preventing data leakage.

The proposed QLSTM architecture adopts a quantum classical hybrid framework. The quantum layer is implemented using a Variational Quantum Circuit executed on a four qubit simulator (N_QUBITS = 4) using the default.qubit device. Classical input features at each time step are encoded into quantum states through Angle Embedding, where input values are mapped into rotational gates. The circuit then applies Basic Entangler Layers with two variational layers (n_layers = 2), enabling parameterized entanglement between qubits. The circuit outputs are obtained by measuring the expectation values of Pauli Z operators on each qubit, producing four quantum features.

These quantum outputs are passed to a fully connected layer that maps the four dimensional quantum measurement results into hidden representations with configurable sizes of 8, 16, or 32 hidden units. A tanh activation function introduces nonlinearity before the final linear output layer generates the predicted stock price. The model processes sequential inputs across time steps, and the final prediction is derived from the last time step representation.

To evaluate the robustness of the architecture, experiments are conducted using five epoch configurations (50, 100, 150, 200, and 250) and four optimization algorithms: SGD, Adam, RMSprop, and Nadam. This systematic configuration enables comprehensive analysis of the interaction between quantum circuit parameters, hidden unit capacity, training duration, and optimization strategy on predictive performance.

2.3 Data Set Splitting

The data segmentation scheme is illustrated in Table 1 and the samplel data can be seen in Table 2.

Table 1. Data Set Split

Data	Splitting	Sum Data	Total Data
Training	80%	1143	1429
Validation	20%	285	

Table 2. Example Data Historical TLKM Share Stock

Date	Close	Open	High	Low	Vol.
30/12/2025	3.510	3.600	3.630	3.500	70,94M
29/12/2025	3.570	3.700	3.700	3.560	48,44M
…….	…….	…….	…….	…….	…….
…….	…….	…….	…….	…….	…….
06/01/2020	3.960	3.930	3.970	3.930	42,91M
03/01/2020	3.980	3.960	3.980	3.930	70,03M
02/01/2020	3.910	3.970	4.000	3.900	52,09M

After preprocessing, the dataset is divided into training and testing sets for model training and evaluation using a consistent split ratio to ensure fair performance measurement and to reduce data leakage risk. The QLSTM model is trained using the training set to learn historical stock price patterns and subsequently applied to generate predictions on the testing set. To improve experimental reliability, each configuration is executed under the same data preprocessing pipeline and normalization scheme so that performance differences are attributable to model parameters rather than data treatment.

The prediction results are analyzed by comparing predicted and actual values using predefined evaluation metrics, including MAE, MSE, RMSE, MAPE, and R^2 Score. In addition to point accuracy, error magnitude and variance are also observed to reflect model stability and generalization behavior. This analysis is conducted across different configurations of training epochs and hidden units to examine their impact on prediction accuracy and stability, as well as to compare the performance of different optimizers, namely Adam, Nadam, SGD, and RMSprop. A structured scenario-based experiment matrix is used so that the effect of each parameter combination can be evaluated systematically.

Finally, conclusions are drawn based on the evaluation results to assess the effectiveness of QLSTM in modeling TLKM stock price movements and to determine the influence of training configurations on prediction quality, providing insights for future applications of quantum machine learning in stock market analysis and for the design of more robust hyperparameter tuning strategies.

3. RESULT AND DISCUSSION

3.1 Model Prediction And Accuracy Result

The prediction results generated by the QLSTM model using different optimizers are first examined through visual analysis to compare the predicted values with the actual data. This visualization provides an initial indication of the model's ability to capture temporal price patterns and highlights differences in prediction behavior across optimizers. The comparative prediction results of the QLSTM model with the SGD, RMSprop, and Adam optimizers are illustrated in Figure 3.

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Figure 3 presents a comparison between actual and predicted open prices generated by the QLSTM model using different optimizers, namely Adam, Nadam, RMSprop, and SGD. The visualization illustrates how each optimizer captures the temporal trend of stock price movements during the testing period. While Adam, Nadam, and RMSprop show predictions that generally follow the actual price trajectory, differences in smoothness and deviation can be observed. In contrast, the SGD-based model exhibits a relatively flatter prediction pattern, indicating limited adaptability to rapid price fluctuations. The Accuracy Result based on MAPE can be seen in Tabel 3 and Figure 4.

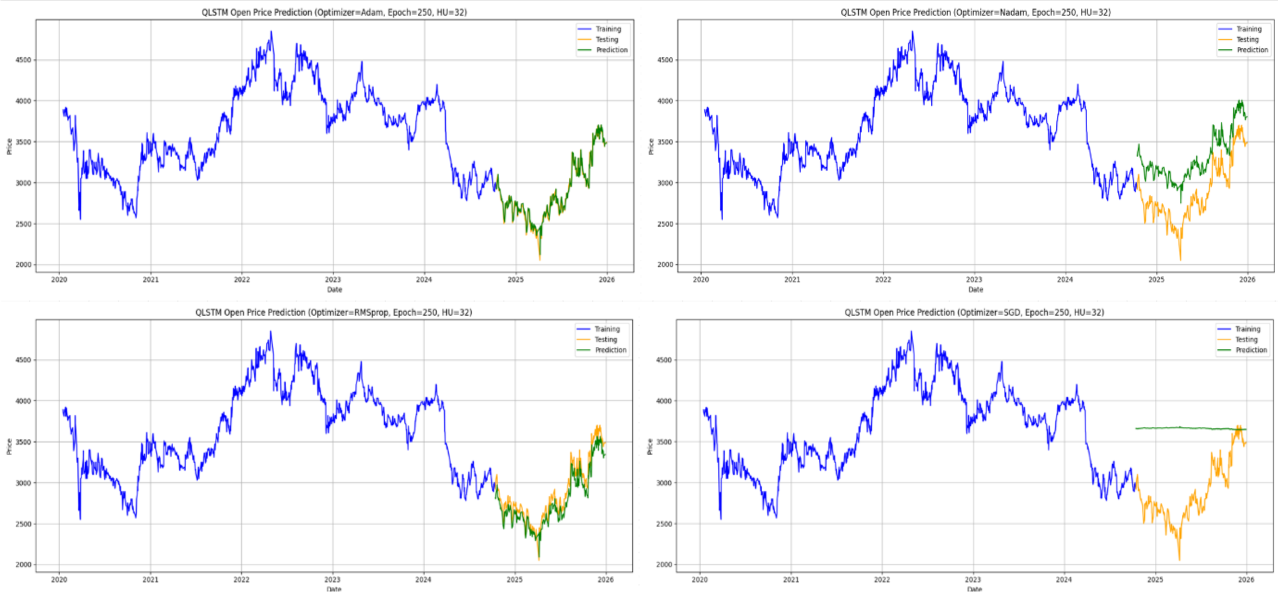

Figure 3. Result of Prediction Graph Every Optimizer (sample using Epoch 250 and , Hidden Unit 32)

Table 3. Accuracy Result

Epoch/Hidden Unit	Accuracy (%)											
	Adam			Nadam			Rmsprop			SGD		
	8	16	32	8	16	32	8	16	32	8	16	32
50	78,04	75,81	83,92	95,40	97,77	87,32	98,12	96,82	96,91	74,72	72,69	73,32
100	97,04	97,22	98,11	92,65	98,13	98,08	97,53	96,70	98,05	76,00	72,94	73,26
150	98,12	97,93	97,10	98,06	98,15	97,57	97,98	95,56	92,61	73,49	73,26	72,00
200	98,00	98,12	98,06	98,15	98,00	94,39	96,51	96,72	96,69	71,88	72,50	77,13
250	98,14	98,14	98,14	98,01	96,96	84,84	96,69	95,22	96,27	73,60	78,03	71,66

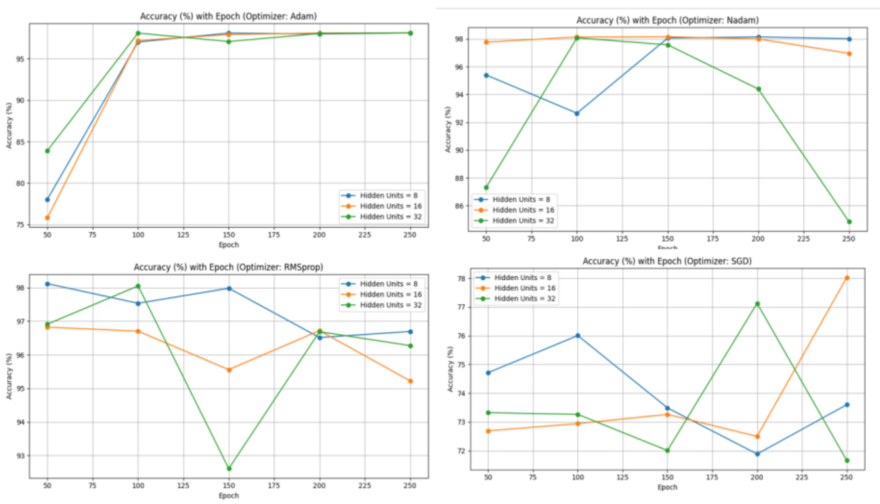

Figure 4. Accuracy Result

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Based on the accuracy results reported in Table 4 and the prediction behavior shown in Figure 4, the Adam optimizer demonstrates a clear improvement as the number of epochs increases. At 50 epochs, Adam achieves accuracies of 78.04%, 75.81%, and 83.92% for 8, 16, and 32 hidden units, respectively. When the epoch count is increased to 100 epochs, the accuracy rises to 97.04–98.11%, and further stabilizes at higher epochs. At 250 epochs, Adam achieves a consistent accuracy of 98.14% across all hidden unit configurations. Similarly, RMSprop shows strong and stable performance, with accuracies ranging from 96.82% to 98.12% at 50 epochs and remaining predominantly above 95% for all configurations up to 250 epochs, where accuracy values of 96.69%, 95.22%, and 96.27% are obtained for 8, 16, and 32 hidden units, respectively. These high accuracy values are reflected in Figure 4, where the predicted prices closely follow the actual price trends.

The Nadam optimizer also exhibits high accuracy across most configurations, achieving peak values of 98.15% at 150 epochs with 16 hidden units and 98.13% at 100 epochs with 16 hidden units. However, a significant decrease in performance is observed at 250 epochs with 32 hidden units, where the accuracy drops to 84.84%, indicating potential overfitting or training instability at higher model complexity. In contrast, the SGD optimizer consistently records the lowest accuracy among all evaluated optimizers, with values ranging from 71.66% to 78.03% across all epoch and hidden unit combinations. Even at the highest epoch setting of 250 epochs, SGD only achieves accuracies of 73.60%, 78.03%, and 71.66% for 8, 16, and 32 hidden units, respectively. This quantitative evidence from Table 4, together with the smoother and less adaptive prediction patterns observed in Figure 4, confirms that adaptive optimizers such as Adam, Nadam, and RMSprop significantly outperform SGD in QLSTM-based stock price prediction tasks.

3.2 Mean Absolute Error (MAE) Result

To further evaluate the predictive performance of the QLSTM model, the mean absolute error (MAE) is employed to quantify the average magnitude of prediction errors without considering their direction. MAE provides an intuitive measure of how closely the predicted values match the actual data, with lower values indicating better prediction accuracy. The MAE results for different optimizers, epoch settings, and hidden unit configurations are summarized in Table 4, while the comparative error patterns are visually illustrated in Figure 5.

Table 4. Mean Absolute Error Result

Epoch/Hidden Unit	Mean Absolute Error											
	Adam			Nadam			Rmsprop			SGD		
	8	16	32	8	16	32	8	16	32	8	16	32
50	593,35	653,97	437,91	125,58	62,62	341,18	53,98	94,50	85,30	681,12	735,61	720,12
100	83,73	78,19	54,01	200,29	53,29	55,06	69,56	96,23	55,77	646,75	730,90	723,37
150	53,70	58,54	79,53	55,55	53,01	68,41	57,76	124,77	210,80	716,53	722,83	756,60
200	56,40	53,60	55,39	53,04	57,89	160,45	99,59	94,91	98,64	760,07	743,28	617,96
250	53,45	53,28	53,19	56,88	86,53	423,21	93,20	135,99	109,67	714,18	593,47	765,84

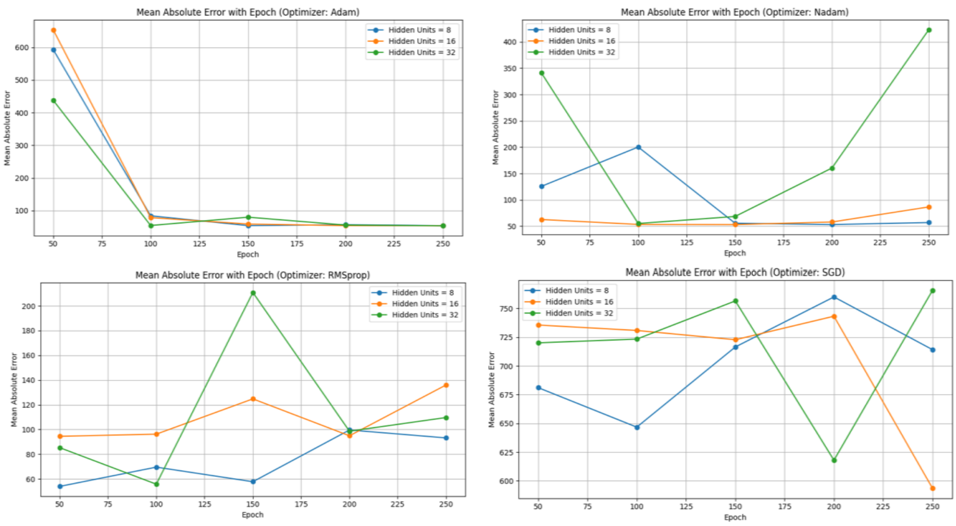

Figure 5. Mean Absolute Error Result

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Based on the MAE values presented in Table 5 and the error distribution illustrated in Figure 5, the performance of the QLSTM model varies significantly across different optimizers, epoch settings, and hidden unit configurations. For the Adam optimizer, a substantial reduction in MAE is observed as the number of epochs increases. At 50 epochs, the MAE values are extremely high, reaching 593.35, 653.97, and 437.91 for 8, 16, and 32 hidden units, respectively. However, at 100 epochs the errors decrease drastically to 83.73, 78.19, and 54.01. The lowest and most stable MAE performance for Adam is achieved at 250 epochs, where the values converge to 53.45, 53.28, and 53.19, indicating strong prediction consistency and improved convergence. The Nadam optimizer demonstrates competitive performance, particularly at 50 and 100 epochs with 16 hidden units, achieving MAE values of 62.62 and 53.29, respectively. The best Nadam performance is observed at 150 epochs with 16 hidden units, reaching 53.01. Nevertheless, instability appears at higher complexity settings, such as 250 epochs with 32 hidden units, where the MAE sharply increases to 423.21, suggesting potential overfitting or training instability.

RMSprop shows moderate but relatively stable MAE values compared to Adam and Nadam. Its lowest error occurs at 50 epochs with 8 hidden units, achieving 53.98, while other configurations fluctuate between approximately 55 and 135. In contrast, the SGD optimizer consistently produces the highest MAE values across all configurations, ranging from 593.47 to 765.84 at 250 epochs and exceeding 680 at 50 epochs. These large error magnitudes indicate poor convergence and inadequate learning capability. Overall, the MAE analysis clearly confirms that adaptive optimizers, particularly Adam and Nadam under appropriate epoch and hidden unit configurations, provide significantly lower prediction errors and more stable learning behavior for QLSTM based stock price forecasting compared to SGD.

3.3 Mean Squared Error (MSE) Result

The robustness of the QLSTM prediction model is further examined using the mean squared error (MSE), which highlights the impact of large deviations between predicted and actual values. By squaring the error terms, MSE becomes particularly sensitive to extreme prediction errors and is therefore effective for evaluating model stability under volatile market conditions. The MSE results for each optimizer across varying epoch and hidden unit configurations are reported in Table 5, while the comparative error behavior of the QLSTM predictions is depicted in Figure 6.

Table 5. Mean Squared Error Result

Epoch/Hidden Unit	Mean Squared Error											
	Adam			Nadam			Rmsprop			SGD		
	8	16	32	8	16	32	8	16	32	8	16	32
50	432146	522809	224960	20596	6634	147951	5482	13574	10633	582341	679333	641323
100	10772	10021	5431	49059	5320	5691	8445	13549	5820	522821	657673	637498
150	5354	6022	10079	5797	5309	8337	6232	20772	49310	629556	639533	702191
200	5756	5351	5766	5287	6369	30431	13513	13215	14565	707612	677719	468988
250	5391	5361	5307	6075	10777	188723	12006	23218	16709	622040	433764	720082

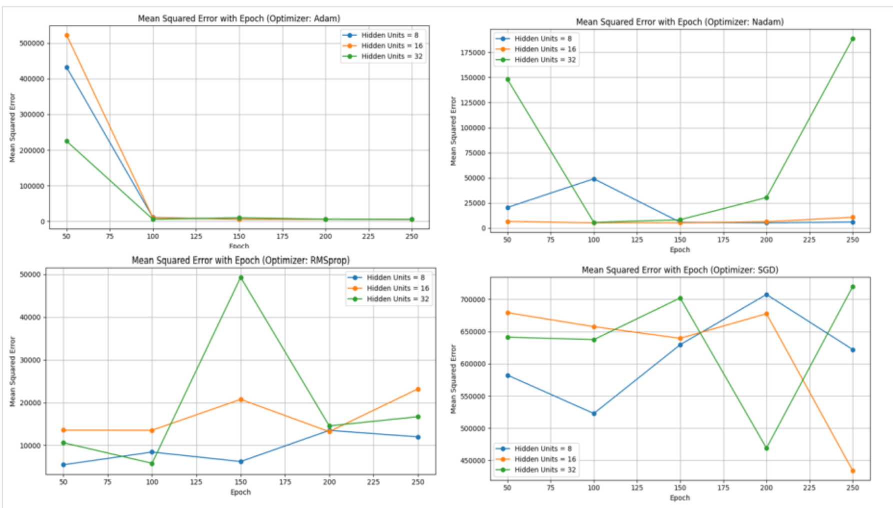

Figure 6. Mean Squared Error Result

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Based on the MSE values presented in Table 5 and the error patterns illustrated in Figure 6, a clear distinction in performance can be observed among the evaluated optimizers. The Adam optimizer shows a substantial reduction in MSE as the number of epochs increases, indicating improved prediction stability. At 50 epochs, Adam records relatively high MSE values of 432,146, 522,809, and 224,960 for 8, 16, and 32 hidden units, respectively. However, at 100 epochs, the MSE drops significantly to 10,772, 10,021, and 5,431, and further stabilizes at higher epochs. At 250 epochs, Adam achieves low and consistent MSE values of 5,391, 5,361, and 5,307 across all hidden unit configurations.

The Nadam optimizer exhibits competitive MSE performance at moderate epoch levels, achieving its lowest value of 5,309 at 150 epochs with 16 hidden units. Nevertheless, a notable increase in MSE is observed at higher model complexity, particularly at 250 epochs with 32 hidden units, where the MSE rises sharply to 188,723, indicating instability or overfitting. RMSprop demonstrates relatively stable performance, with MSE values generally remaining below 25,000 across most configurations, including 12,006, 23,218, and 16,709 at 250 epochs for 8, 16, and 32 hidden units, respectively. In contrast, the SGD optimizer consistently produces the largest MSE values, ranging from 433,764 to 720,082 at 250 epochs, and exceeding 500,000 in most configurations. This confirms that SGD struggles to minimize large prediction errors, a behavior that is clearly visible in Figure 6 through wider error dispersion.

3.4 Root Mean Squared Error (RMSE) Result

While MAE and MSE provide useful insights into average and squared prediction errors, the root mean squared error (RMSE) is employed to express prediction error magnitude in the same scale as the original data, making it more interpretable in practical forecasting scenarios. RMSE emphasizes larger deviations while maintaining unit consistency, allowing a clearer assessment of how far the predicted values deviate from actual observations. The RMSE results obtained from different optimizers under varying epoch and hidden unit configurations are summarized in Table 6, with the corresponding error trends illustrated in Figure 7.

Table 6. Root Mean Squared Error Result

Epoch/Hidden Unit	Root Mean Squared Error											
	Adam			Nadam			Rmsprop			SGD		
	8	16	32	8	16	32	8	16	32	8	16	32
50	657,4	723,1	474,3	143,5	81,5	384,6	74,0	116,5	103,1	763,1	824,2	800,8
100	103,8	100,1	73,7	221,5	72,9	75,4	91,9	116,4	76,3	723,1	811,0	798,4
150	73,2	77,6	100,4	76,1	72,9	91,3	78,9	144,1	222,1	793,4	799,7	838,0
200	75,9	73,1	75,9	72,7	79,8	174,4	116,2	115,0	120,7	841,2	823,2	684,8
250	73,4	73,2	72,8	77,9	103,8	434,4	109,6	152,4	129,3	788,7	658,6	848,6

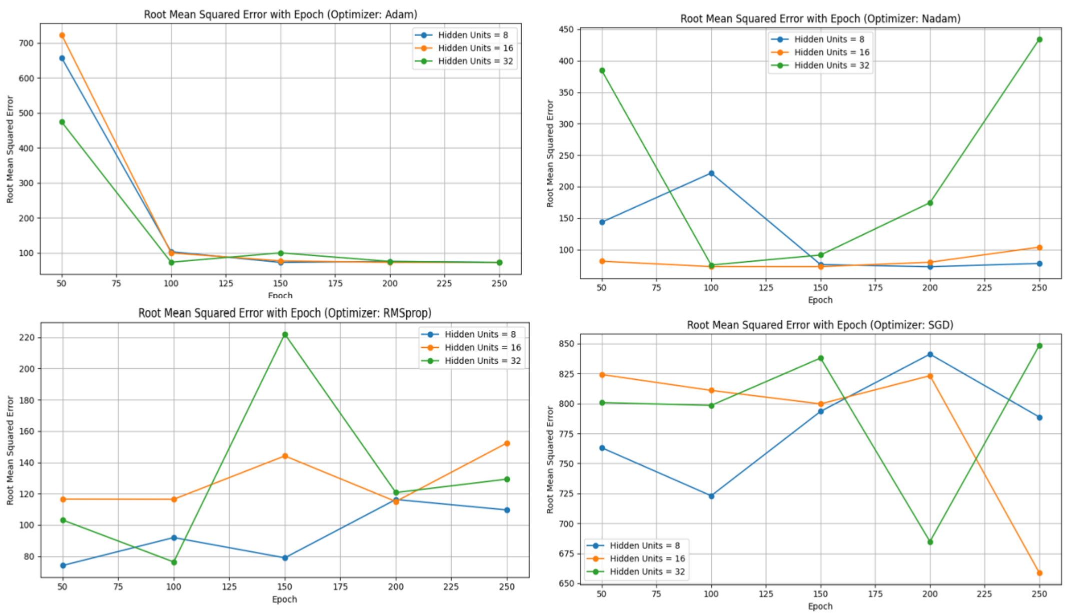

Figure 7. Root Mean Squared Error Result

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Based on the detailed results, the Adam optimizer shows a clear reduction in RMSE as training progresses, with values decreasing from 657.4–723.1 at 50 epochs to 73.4–72.8 at 250 epochs across all hidden unit settings. Nadam achieves competitive RMSE values at moderate configurations, reaching as low as 72.9 at 100 and 150 epochs with 16 hidden units, but exhibits a sharp increase to 434.4 at 250 epochs with 32 hidden units, indicating potential instability at higher complexity. RMSprop maintains relatively consistent RMSE values, generally remaining below 130 for most configurations, while the SGD optimizer consistently produces the highest RMSE values, exceeding 650 across all epoch and hidden unit combinations. These results, as also observed in Figure 7, confirm that adaptive optimizers such as Adam and RMSprop are more effective in minimizing large prediction errors in QLSTM-based stock price forecasting.

3.5 Mean Absolute Percentage Error (MAPE) Result

To complement the absolute and squared error evaluations, the mean absolute percentage error (MAPE) is employed to measure prediction accuracy in relative terms by expressing the error as a percentage of the actual values. MAPE provides an intuitive interpretation of model performance, as it reflects the average percentage deviation between predicted and actual prices regardless of scale. This metric is particularly useful for comparing forecasting accuracy across different model configurations. The MAPE results for each optimizer under varying epoch and hidden unit settings are presented in Table 7, with the corresponding percentage error patterns illustrated in Figure 8.

Table 7. Mean Average Percentage Error Result

	Mean Average Percentage Error (%)											
	Adam			Nadam			Rmsprop			SGD		
Epoch/Hidden Unit	8	16	32	8	16	32	8	16	32	8	16	32
50	22,0	24,2	16,1	4,6	2,2	12,7	1,9	3,2	3,1	25,3	27,3	26,7
100	3,0	2,8	1,9	7,3	1,9	1,9	2,5	3,3	1,9	24,0	27,1	26,7
150	1,9	2,1	2,9	1,9	1,8	2,4	2,0	4,4	7,4	26,5	26,7	28,0
200	2,0	1,9	1,9	1,9	2,0	5,6	3,5	3,3	3,3	28,1	27,5	22,9
250	1,9	1,9	1,9	2,0	3,0	15,2	3,3	4,8	3,7	26,4	22,0	28,3

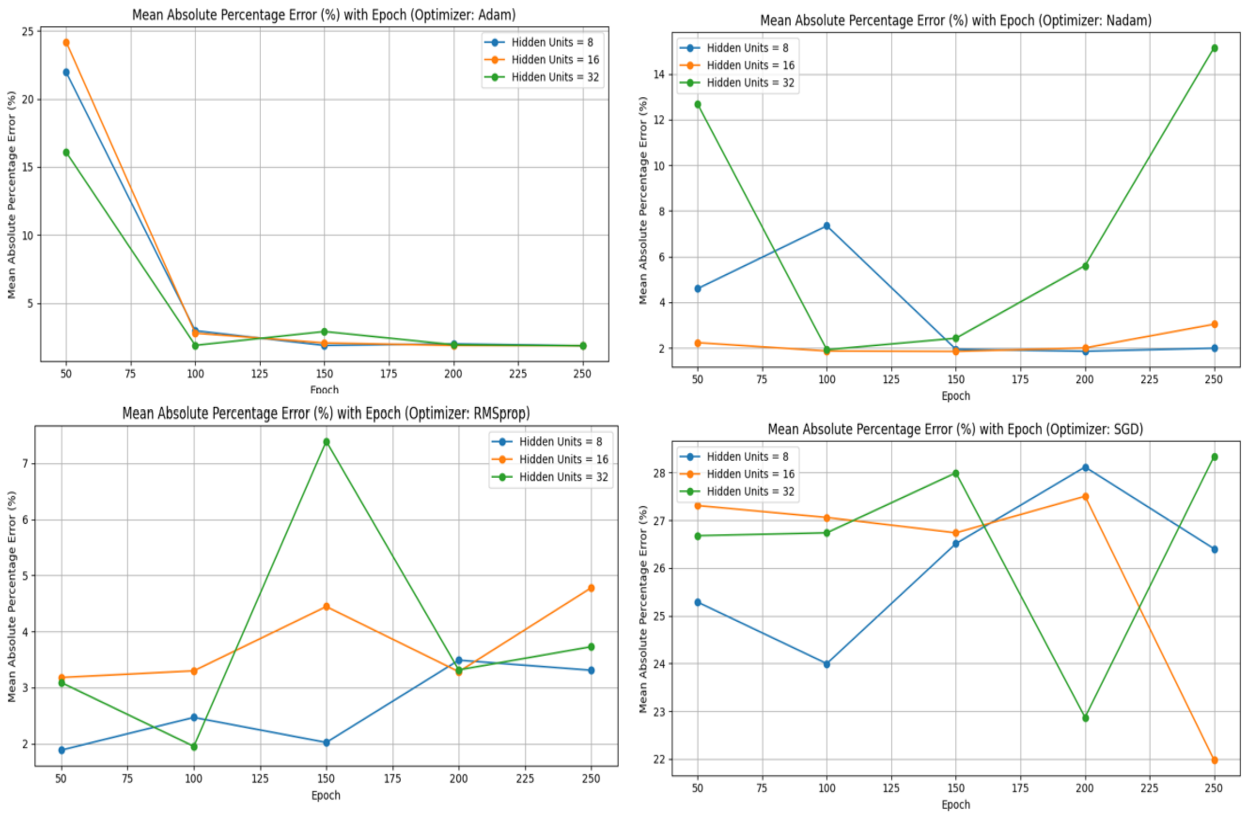

Figure 8. Mean Average Percentage Error Result

Based on the MAPE values reported in Table 7 and the percentage error patterns illustrated in Figure 8, the relative prediction accuracy of the QLSTM model varies substantially across different optimizers and training configurations. For the Adam optimizer, the MAPE decreases sharply as the number of epochs increases, from relatively high values of 22.0%, 24.2%, and 16.1% at 50 epochs to consistently low values of 1.9% across all hidden unit settings at 250 epochs. This indicates a significant improvement in relative prediction accuracy with extended

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training. Nadam exhibits competitive performance, achieving its lowest MAPE values of 1.8% and 1.9% at 150 and 200 epochs with 16 hidden units, although a notable increase to 15.2% is observed at 250 epochs with 32 hidden units, suggesting sensitivity to increased model complexity. RMSprop maintains relatively stable MAPE values across most configurations, generally remaining between 1.9% and 4.8%, while the SGD optimizer consistently produces the highest MAPE values, ranging from 22.0% to 28.3% across all epoch and hidden unit combinations. These results, as also reflected in Figure 8, confirm that adaptive optimizers such as Adam, Nadam, and RMSprop provide substantially lower relative prediction errors compared to SGD in QLSTM-based stock price forecasting.

3.6 R^2 Score Result

To evaluate the goodness of fit between the predicted and actual stock prices, the coefficient of determination (R^2 score) is employed to measure how well the QLSTM model explains the variance in the observed data. The R^2 score provides insight into the explanatory power of the prediction model, where values closer to one indicate a stronger ability to capture the underlying price dynamics. The R^2 results obtained for different optimizers under varying epoch and hidden unit configurations are summarized in Table 8, with the corresponding model fitting behavior illustrated in Figure 9.

Table 8. R^2 score Result

	R^2 score											
	Adam			Nadam			Rmsprop			SGD		
Epoch/Hidden Unit	8	16	32	8	16	32	8	16	32	8	16	32
50	-2,31	-3,01	-0,73	0,84	0,95	-0,13	0,96	0,90	0,92	-3,47	-4,21	-3,92
100	0,92	0,92	0,96	0,62	0,96	0,96	0,94	0,90	0,96	-3,01	-4,04	-3,89
150	0,96	0,95	0,92	0,96	0,96	0,94	0,95	0,84	0,62	-3,83	-3,91	-4,39
200	0,96	0,96	0,96	0,96	0,95	0,77	0,90	0,90	0,89	-4,43	-4,20	-2,60
250	0,96	0,96	0,96	0,95	0,92	-0,45	0,91	0,82	0,87	-3,77	-2,33	-4,52

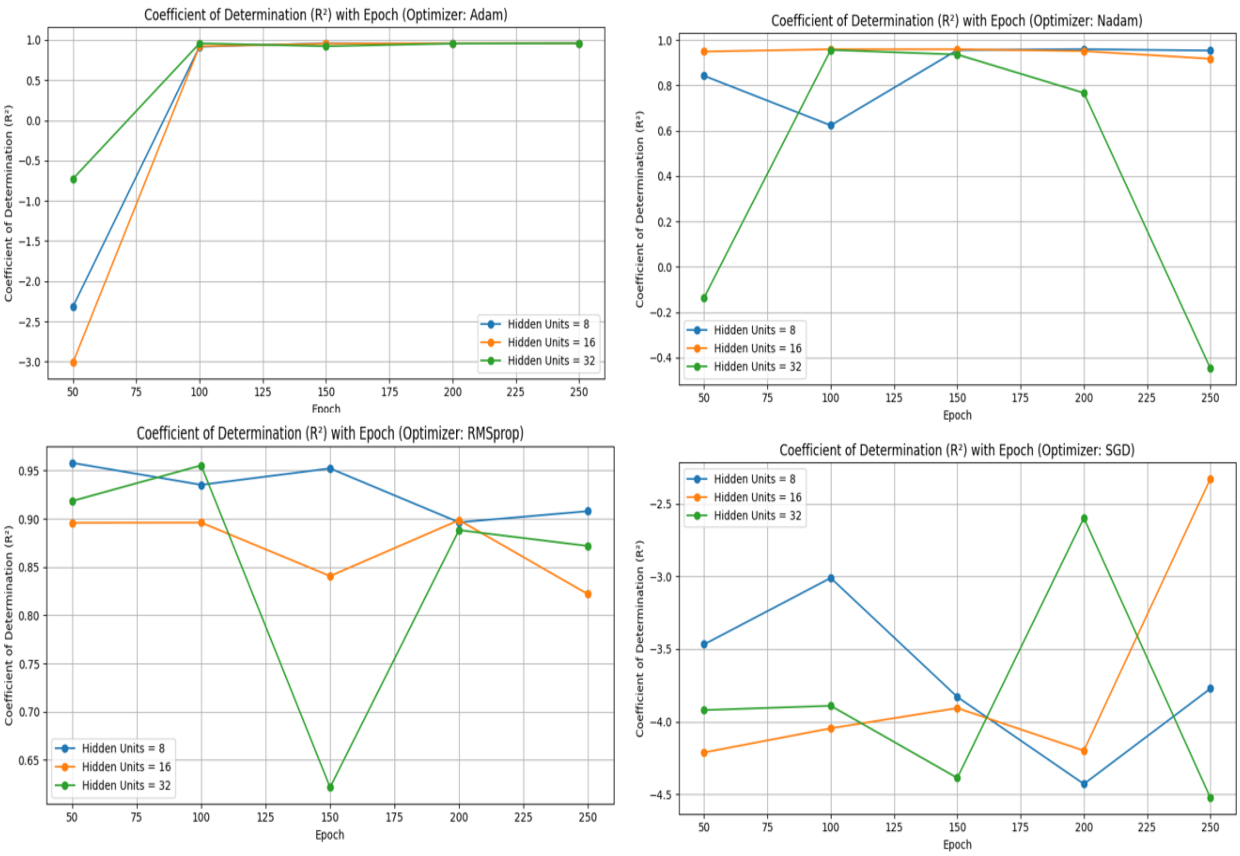

Figure 9. R^2 score Result

Based on the R^2 score values reported in Table 8 and the fitting behavior illustrated in Figure 9, the explanatory capability of the QLSTM model is strongly affected by the choice of optimizer and training configuration. For the Adam optimizer, negative R^2 values are observed at 50 epochs, with values of −2.31, −3.01, and −0.73 for 8, 16, and 32 hidden units, indicating poor model fit at early training stages. However, as the number of epochs increases, the R^2 score improves substantially, reaching stable and high values of 0.96 across all hidden unit configurations at 150, 200,

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and 250 epochs. This demonstrates that Adam effectively captures the variance of stock price movements after sufficient training.

The Nadam optimizer shows a similar trend, achieving high R^2 values of up to 0.96 at 100 and 150 epochs with 16 and 32 hidden units, although performance degradation is observed at higher complexity, where the R^2 score drops to −0.45 at 250 epochs with 32 hidden units. RMSprop maintains relatively consistent performance, with R^2 values ranging from 0.90 to 0.96 across most configurations, indicating a stable goodness of fit between predicted and actual prices. In contrast, the SGD optimizer consistently produces negative R^2 scores across all epoch and hidden unit combinations, ranging from −2.33 to −4.52, which indicates that the model performs worse than a baseline mean predictor. These results, as also reflected in Figure 9, confirm that adaptive optimizers such as Adam, Nadam, and RMSprop significantly outperform SGD in terms of variance explanation and overall model fitting in QLSTM-based stock price prediction.

4. CONCLUSION

Overall, the evaluation results demonstrate that the performance of the QLSTM model is highly dependent on the selected optimizer and training configuration, which aligns with the experimental scope described in the abstract. This also addresses a research gap, since systematic optimizer-level analysis on QLSTM with controlled variations of epochs (50–250) and hidden units (8, 16, 32) is still rarely reported. Based on accuracy, error-based metrics (MAE, MSE, RMSE, and MAPE), and goodness-of-fit evaluation using the R^2 score, adaptive optimizers consistently outperform conventional SGD. Adam achieves the best overall performance, with accuracy based on MAPE reaching 98.14%, RMSE decreasing to about 72.8, MAPE around 1.9%, and a stable R^2 score near 0.96 at 250 epochs. RMSprop also shows robust and consistent results, maintaining accuracy above 95% with R^2 values in the range of approximately 0.90–0.96. Nadam delivers competitive performance at moderate epoch and hidden unit settings but shows degradation at higher complexity configurations, indicating sensitivity to overtraining and reinforcing the need for structured hyperparameter evaluation. In contrast, SGD records accuracy below 80%, RMSE values exceeding 650, and consistently negative R^2 scores down to about −4.52, confirming its limited capability in modeling nonlinear and dynamic stock price movements. These results emphasize that adaptive optimizers combined with proper hyperparameter settings are critical for achieving accurate and stable QLSTM-based stock price predictions.

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