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FORECASTING WEEK-AHEAD CLOSING PRICE OF MUSCAT SECURITIES MARKET USING HYBRID TCN-LSTM MODEL

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ABSTRACT

Accurately forecasting financial time-series data is a challenging task due to the dynamic and volatile nature of stock markets. This study introduces a hybrid Temporal Convolutional Network (TCN) and Long Short-Term Memory (LSTM) model designed to improve stock price forecasting for the Muscat Securities Market (MSM). Unlike standalone deep learning models, this hybrid approach effectively captures both short-term and long-term dependencies, leading to improved predictive accuracy. Trained on 24 years of historical MSM data (2000–2024), the model was evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The hybrid model outperformed both standalone architectures, achieving the lowest MAE (206.29) and RMSE (314.31).

This research advances financial forecasting by introducing a hybrid TCN-LSTM model specifically optimized for the Muscat Securities Market (MSM), a relatively underexplored financial domain. The study bridges the gap in existing models by enhancing predictive performance through an innovative fusion of deep learning techniques. The study contributes to financial forecasting research by demonstrating how hybrid deep learning models can enhance market prediction accuracy, providing valuable insights for investors and financial analysts. Future research directions include the integration of adaptive learning mechanisms and external financial indicators for further performance enhancement.

Keywords: *Muscat Securities Market, Stock Price Prediction, Hybrid Tcn-Lstm, Financial Time-Series Forecasting, Deep Learni*ng

1. INTRODUCTION

Predicting stock market trends has always been a tough challenge because financial markets are unpredictable, tough changing, and complex tasks. Traditional methods often struggle to make sense of the intricate relationships in stock data, which is why more advanced deep-learning techniques have gained popularity. With the rise of artificial intelligence (AI), forecasting financial trends has become more accurate and reliable [1]–[5]. Stock market forecasting remains a complex challenge due to the dynamic and nonlinear nature of financial markets. Traditional statistical models often fail to capture these dependencies, necessitating advanced machine-learning techniques. The rise of deep learning has provided new opportunities for enhancing predictive accuracy in financial time-series forecasting [6]. Stock market price prediction is an important research direction in the realm of financial analysis given that its implications are related to both investment decisions and economic growth. The precise stock price prediction not only helps investors make informed decisions but also contributes to the effective functioning of financial markets. As one of Oman's major stock exchanges, the Muscat Securities Market (MSM) captures the momentum of the region's economy. Yet forecasting stock price movements in MSM is complicated by the chaotic and nonlinear nature of stock movements. The field of time series forecasting has seen a tremendous transformation in the last few years due to the evolution of machine learning and deep learning models.

Among the different AI-driven approaches, Long Short-Term Memory (LSTM)

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networks and Temporal Convolutional Networks (TCN) have stood out for their ability to recognize patterns and trends in stock market data [3], [7]–[9].

LSTM networks, a specialized form of recurrent neural networks (RNNs), are great at spotting long-term trends because they avoid the common issue of forgetting important information over time. This makes them particularly useful for analyzing stock market movements [8]–[10]. On the other hand, TCNs use a different technique, focusing on short-term fluctuations through advanced convolutional operations. Each has its strengths and weaknesses: LSTM is better for long-term trends, while TCN is more effective for short-term changes [11], [12].

Hybrid models, which integrate multiple deep learning architectures such as TCN and LSTM networks, offer significant advantages in various sequential data processing tasks[6]. One of the primary benefits of hybrid models is their ability to leverage the strengths of different architectures, compensating for the weaknesses of individual models. For instance, TCN excels at capturing short-term dependencies through causal dilated convolutions, while LSTM effectively retains long-term dependencies using memory cells. By combining these approaches, hybrid models achieve a balanced representation of temporal features, leading to enhanced predictive accuracy in tasks such as financial forecasting, speech recognition, and anomaly detection [13].

1.1 Problem Statement

Despite advancements in financial forecasting, existing stock prediction models suffer from either inadequate short-term sensitivity (LSTM) or lack of long-term retention (TCN). MSM, as a relatively under-researched financial market, lacks advanced forecasting models tailored to its unique dynamics. This study aims to fill this gap by proposing and evaluating a hybrid deep learning model that integrates TCN and LSTM, ensuring improved market trend analysis and investor decision-making capabilities.

1.2 Hypothesis

A hybrid TCN-LSTM model will demonstrate superior predictive performance over standalone TCN and LSTM models in forecasting MSM weekly closing prices.

1.3 Study Goal and Contribution

The goal of this study is to improve the accuracy of stock market forecasts by predicting the closing price of the Muscat Securities Market (MSM) one week in advance. To achieve this, we propose a hybrid deep learning model that combines TCN and LSTM architectures. By blending the strengths of both models, we aim to create a more balanced and precise forecasting method that can better capture market trends and fluctuations.

2 LITERATURE REVIEW

Forecasting stock prices accurately is still one of the major problems in finance. The stock market is highly affected by many factors, such as macroeconomic indicators, geopolitical events, investor sentiment, and news related to companies. Traditional econometric models have been used, but they do not capture non-linearity or long-term dependencies in financial time series data, which are well-known limitations. This literature systematically reviews articles on stock price prediction between 2010 to 2024. The papers were selected based on their relevance to the current topic, rigour in methodology and diversity of employed techniques. The comparison emphasizes important features such as model type, type of data used, method, results and stock price prediction contribution by the works. This structured methodology provides a framework for comparison between the methodologies and their efficacy in predicting stock prices. Some studies used standard time series models (e.g. Arima generalized autoregressive integrated moving average) for predicting stock prices. Although ARIMA models are straightforward and interpretable, their assumptions of linearity and stationarity often restrict the ability of these models to accurately capture the complex non-linear behaviour of stock markets. In [14] authors used LSTM networks to forecast the NIFTY 50 index which demonstrated efficient long-term dependencies in sequential data. Still, LSTMs may be computationally

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expensive, especially if one works with a large dataset and a long time horizon. On the other hand, Convolutional Neural Networks (CNNs) are particularly powerful in extracting features from spatial data, which can be adapted to time series by interpreting time as a spatial dimension. For example, Wang [15] created CNN models for short-term (weekly) and medium-term (three-month) stock price prediction, highlighting CNNs' versatility to various time horizons. The results demonstrated how CNNs can learn both short- and long-term patterns and adapt to varying prediction horizons. For example, Zhao, Hao and Li [16] also used a hybrid CNN-LSTM model for stock price prediction, showing that CNN is good at feature extraction and LSTM can solve the long-term dependence problem. Their hybrid model, which employs a combination of CNN and LSTM, successfully captures both short-term patterns (through CNN) and long-term dependencies (through LSTM). Of course, while LSTMs and CNNs are powerful, the choice between the two types of networks and any potential combination thereof depends heavily on the context in which you are working.

Aware of the constraints of single-model methods, an increasing number of academics have investigated hybrid architectures that synergize the advantages of various models. Hybridization is one option where one can benefit from local features and short-term aspect capturing of Temporal Convolution Networks (TCN) and the long-term dependencies and background trends maintaining the capacity of Long Short-Term Memory (LSTM). In [17], a new TCN-LSTM hybrid model was introduced by Purba and Pasha, and TCN-LSTM provided the highest accuracy among the performance results of other combined configurations. They did, however, offer comparisons of different hybrid model configurations, affording insights into the criticality of model architecture design. The TCN-LSTM hybrid model consistently outperformed classical approaches in terms of prediction accuracy. Some studies combined LSTM with other models such as ARIMA or Random Forest, highlighting the strength of hybrid models. A few papers tried to improve stock price prediction efficiency by advanced techniques. Some of these techniques include Bayesian Optimization for hyperparameter tuning, attention mechanisms, and ensemble methods. Qian [18] applied Bayesian optimization to optimize the hyperparameters of a hybrid CNN-LSTM model, resulting in better prediction accuracy and stability on all loss functions. This approach allowed us to effectively search the hyperparameter space and acquire an optimized model with enhanced performance due to the application of Bayesian optimization. For example, in their Bi-LSTM-ATT model, Niu, Pan and Xu added an attention mechanism to predict the price of Chinese stock better, proving that concentrating on the most relevant part of the input was advantageous. These words might be closer to the ones you know if only a little. Ahmed Khattak et al. [19] predicted that more sophisticated ensemble and hybrid models that use LSTM and SVM will be favoured in forecasting financial trends and prices. Ensemble methods can help lift the limitations on individual model performance by aggregating predictions from various models to increase overall accuracy and robustness. The slight difference spiel on an overall improvement might look obvious by finding early stages for such characters great discussed only on them every improving before performance could be such from numbers in lots of characters which improve the numbers of final or advanced models. The impact of investor sentiment on stock prices has been well established. Some papers incorporated sentiment analysis, often from news articles or social media, to improve prediction performance. Chen and Kawashima [20] studied using recent news sentiment estimation based on large language models, in conjunction with the new transformer-based prediction models, for stock price prediction. The study showed that the use of large language models is promising for stock price prediction based on sentiment. Meanwhile, based on the Chinese A-share market, Niu, Pan and Xu explored the influence of multi-classification investors' sentiment on stock price prediction and also proved that incorporation with sentiment indicators would improve the accuracy of the model. These studies are a clear indication of the need to take into account not only quantitative data but also qualitative data to obtain a better overall picture of the market. Other papers take special approaches to stock price prediction. Jia, Anaissi and Suleiman [21] proposed the ResNLS model, a hybrid ResNet-LSTM architecture that outperforms most baseline models in SSE Composite Index prediction. They focused on how stock prices are dependent to different degrees on one another. Wang et al.[22], proposed a multivariate LSTM-CNN model to predict the price of grain commodities, which included weather data, macroeconomic data, and a snow factor. Their work is an example of how climate data can be applied to commodity price forecasting. Sun et al. [23] In this, an integrated strategy involving Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), Long Short-Term Memory (LSTM), and the ensemble learning algorithm LightGBM was developed, which can simultaneously increase the prediction of fitting precision. In a paper by [24], an effective stock market forecasting framework based on improved holistic learning principles using LSTM and ARIMA models with data segmentation was proposed. Which showed more appropriate prediction struggles than ARIMA, LSTM, and GRU. Xu et al. [25] proposed a Temporal Convolutional Networks-Generative Adversarial Nets (TGAN) model, demonstrating superior prediction accuracy compared to ARIMA, LSTM, and GRU models. These diverse approaches showcase the ongoing innovation and exploration within the field, pushing the boundaries of stock price prediction methodologies. This variety of methodologies highlights how innovation in stock price prediction continues to be an area of exploration in space, with each approach having its merits. This study analyses time-series stock data, with opening and close prices as well as price changes, volume and adjusted closing values for each day. They are available from Yahoo!

2.1 Research Gap

While there has been a lot of progress in predicting financial time series, one of the hardest problems remains stock market trend prediction due to fluctuations in the market and non-linear relations. More recent studies have used a range of sequence-based deep learning architectures (e.g., Long Short-Term Memory (LSTM) networks and convolutional Neural Networks (CNNs)) and have demonstrated success in terms of capturing temporal relationships. But standalone models either do well at short-term feature extraction or long-term sequence retention, not both. The TCN-LSTM combinations, known as hybrid models, were successful in predicting accuracy by combining the advantages of both architectures. For the MSM, however, few studies applied these hybrid models. In this study, we address this research gap by benchmarking a hybrid TCN-LSTM model against baselines in the form of standalone TCN and LSTM architectures to see if hybridization is beneficial for weekly stock prediction for MSM. This contributes to the state of the art in stock market forecasting models by addressing issues of both short- and long-range dependencies which are considered as main challenges in the successful development of any type of consistent models.

3 METHODOLOGY

In this study, the researchers systematically evaluated the performance of three distinct model architectures. Standalone TCN, LSTM networks, and a hybrid TCN-LSTM model by conducting a series of experiments, testing each model individually to assess its ability to capture temporal dependencies and optimize sequential learning. This research advances financial forecasting by introducing a hybrid TCN-LSTM model specifically optimized for the Muscat Securities Market (MSM), a relatively underexplored financial domain. The study bridges the gap in existing models by enhancing predictive performance through an innovative fusion of deep learning techniques.

3.1 Data Collection and Preprocessing

For our analysis, we utilized a comprehensive dataset spanning 24 years, from 2000 to 2024, obtained from Investing.com. This dataset encompasses daily historical data for the Muscat Securities Market (MSM), including crucial metrics such as daily prices, opening and closing values, highs and lows, trading volume, and percentage changes. The long-time frame provides a robust foundation for understanding market trends, identifying cyclical patterns, and assessing the impact of significant financial events over the past two decades. By leveraging this extensive dataset, we can generate insightful analyses, develop predictive models, and form data-driven investment strategies, providing a solid basis for our financial research [26]. In data processing, to improve predictive accuracy, additional features were extracted, including:

- Standard deviation of high, low, and closing prices to capture market volatility.
- The price range (high-low difference) is a potential indicator of market activity.

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The inclusion of the high-low price difference aims to provide the model with more data points to learn from, potentially reflecting market volatility and trading volume trends. However, the direct relationship between this feature and next week's closing price is not inherently strong. Future work could validate its effectiveness by conducting correlation analysis and feature importance evaluation to determine whether it significantly contributes to model accuracy.

3.2 Model Experiments and Performance Evaluation

This study evaluates the predictive performance of three different model architectures. Standalone TCN, standalone LSTM networks, and a hybrid TCN-LSTM model for forecasting the weekly closing rate of the Muscat Securities Market (MSM). The models were trained and tested on the selected dataset. Each model was trained for 100 epochs, using Mean Squared Error (MSE) as the loss function and an adaptive optimizer for improved convergence.

3.2.1 Evaluation Metrics and Model Training

The models were trained using the Adam optimizer with a mean squared error (MSE) loss function, employing 128 filters and a learning rate of 0.001 to ensure stable convergence. Each model—standalone TCN, standalone LSTM, and the hybrid TCN-LSTM model—was optimized over 100 epochs to effectively capture temporal dependencies and predict the weekly closing rate of the Muscat Securities Market (MSM).

To assess model performance, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) were used as evaluation metrics. RMSE measures the standard deviation of the residuals, providing insight into how well the model generalizes, while MAE quantifies the average magnitude of prediction errors, indicating overall accuracy. The lower the RMSE and MAE values, the better the model's predictive performance. Figure 1 illustrates the testing and prediction performance, demonstrating how well each model aligns with actual market trends. The comparative evaluation of these metrics highlights the effectiveness of each architecture in capturing market fluctuations, with the hybrid model showing improved predictive accuracy over standalone models.

3.2.2 Testing standalone TCN

The TCN model utilized causal dilated convolutions to capture both short-term and long-term temporal dependencies while maintaining the sequential order of financial data. The model's structure incorporated multiple convolutional layers with exponentially increasing dilation factors, enabling it to learn patterns across different time scales. The model utilizes an exponentially growing dilation pattern [1,2,4,8,16,32,64,128] to capture both short-term fluctuations and long-term dependencies in financial time-series data. Smaller dilations focus on local price variations, while larger dilations expand the receptive field, allowing the model to retain essential market trends over extended periods. This hierarchical structure ensures a comprehensive understanding of temporal patterns across multiple time scales. Moreover, the dropout rate was tested between (0.05 to 0.3) and fixed at 0.2 to ensure that the model learn temporal dependencies while reducing unnecessary noise. Figure 1 illustrates the testing and prediction performance, comparing actual closing rates with predicted values. The results show that TCN effectively captures market trends, particularly short-term fluctuations, with strong generalization capabilities.

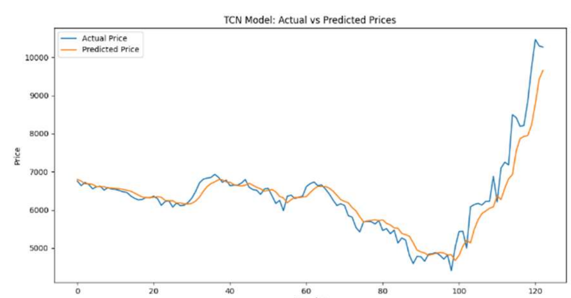

Figure 1: Actual vs Predict performance of TCN model

3.2.3 Testing Standalone LSTM

The standalone LSTM model was implemented to assess the effectiveness of gated recurrent units in retaining long-term dependencies within financial time series data. The model comprised multiple stacked LSTM layers, which processed sequential data by

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selectively storing and forgetting information over time. Similar to TCN, The number of LSTM units is a critical hyperparameter that influences the model's ability to capture long-term dependencies in financial time-series data. To determine the optimal configuration, three different values (32, 64, and 128 units) were tested, and their impact on model performance was analyzed. Based on these experiments, 128 LSTM units were chosen as the optimal configuration for the final model. Figure 2 presents the testing and prediction performance of the LSTM model, highlighting its ability to learn long-term patterns in stock market trends.

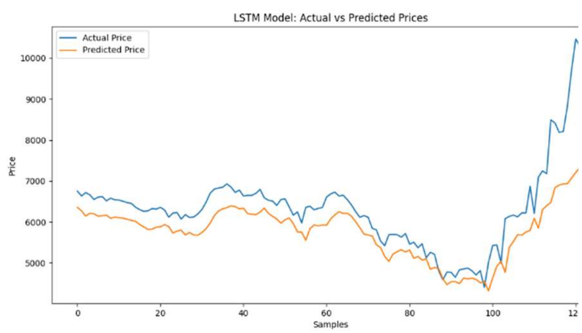

Figure 2: Actual vs Predict performance of the LSTM model

3.3.3 Hybrid TCN-LSTM Model

To leverage the strengths of both Temporal Convolutional Networks (TCN) and Long Short-Term Memory (LSTM) networks, a hybrid model incorporating alternating TCN and LSTM layers was developed. This architecture combines TCN's ability to extract convolutional features with LSTM's capability to retain long-term sequential dependencies, ensuring a comprehensive learning framework for temporal modelling. In this design, the output of each TCN layer is fed into the subsequent LSTM layer, and vice versa, establishing a densely interconnected structure that enhances predictive accuracy by facilitating robust information flow.

The proposed hybrid model consists of four TCN layers interleaved with four LSTM layers to capture both localized temporal dependencies and long-range sequential patterns. Each TCN block employs causal dilated convolutions, preserving the sequential order of the input data while incorporating residual connections to maintain stable gradient propagation. Following each TCN block, an LSTM layer processes the extracted features, utilizing gated recurrent units to effectively retain long-term dependencies and mitigate vanishing gradient issues. The dense interconnection mechanism ensures that the output of each block is propagated forward to all subsequent layers, fostering comprehensive feature sharing and progressive refinement throughout the network.

This structured integration of TCN and LSTM enables the model to effectively balance short-term feature extraction and long-term sequence retention, optimizing its predictive capability for complex temporal modelling tasks. The final recurrent layer consolidates the extracted temporal features before passing them through a fully connected layer, which applies an appropriate activation function depending on the specific task. This design ensures robust performance in time-series forecasting, anomaly detection, and sequential decision-making applications. Figure 3 presents the structural diagram of the hybrid model, illustrating its layered composition and interconnections.

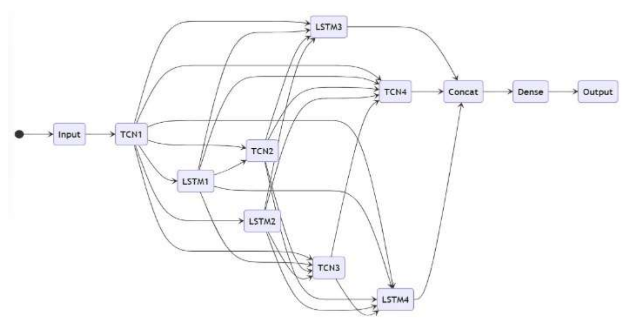

Figure 3: Hybrid model architecture

3.3.3 Testing Hybrid TCN-LSTM Model

The Model trained for 100 epochs, the hybrid model demonstrated superior performance in testing and prediction tasks, as shown in Figure 4, with improved trend identification and reduced error margins compared to standalone models. The experimental results provide a comparative analysis of the three architectures, demonstrating that TCN excels at short-term fluctuations, LSTM captures long-term trends, and the hybrid model achieves a balanced, optimized prediction capability.

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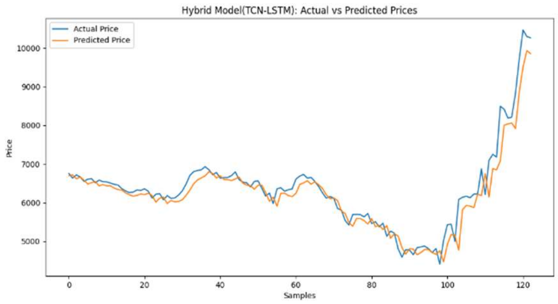

Figure 4: Actual vs Predict performance of the Hybrid model

4 RESULTS AND DISCUSSION

This section presents the comparative performance analysis of the three tested models TCN, LSTM, and the hybrid TCN-LSTM model based on their ability to predict the weekly closing rate of the MSM. The models were evaluated using MAE and RMSE as performance metrics. The results, summarized in Table 1, highlight significant differences in predictive accuracy among the three architectures.

Table 1 presents the comparative performance of the models.

Model	MAE	RMSE
TCN	230.52	380.18
LSTM	558.92	776.95
Hybrid TCN-LSTM	**206.29**	**314.31**

4.1 Comparative Model Performance

As shown in Table 1, the hybrid TCN-LSTM model achieved the lowest MAE (206.29) and RMSE (314.31), indicating superior predictive performance compared to the standalone models. The TCN model demonstrated moderate accuracy, with an MAE of 230.52 and RMSE of 380.18, outperforming the LSTM model, which exhibited the highest prediction errors (MAE: 558.92, RMSE: 776.95). These findings suggest that while both TCN and LSTM contribute to effective time-series forecasting, their combination in a hybrid architecture yields greater accuracy and improved generalization.

4.2 Discussion of Model Performance

The superior performance of the hybrid TCN-LSTM model can be attributed to its ability to leverage the strengths of both architectures. The TCN layers efficiently capture short-term temporal dependencies using causal dilated convolutions, while the LSTM layers retain long-term dependencies, preventing information loss over extended sequences. The dense interconnection mechanism in the hybrid model further enhances feature propagation, allowing for more refined sequential learning. In contrast, the standalone TCN model performed better than the standalone LSTM model, likely due to TCN's capability to process sequential data in parallel, reducing the impact of vanishing gradients and ensuring a stable learning process. However, because TCN primarily relies on convolutional filters, it may struggle with long-range dependencies, which explains why its performance was slightly inferior to the hybrid model. The LSTM model, on the other hand, exhibited the highest error rates, suggesting challenges in capturing fine-grained short-term patterns while maintaining long-term sequence dependencies. LSTM's sequential processing nature makes it computationally intensive and prone to vanishing gradients, particularly in deep architectures, which may have contributed to its lower predictive accuracy.

4.3 Comparison with Existing Studies and Research Contribution

Several studies have explored LSTM-based or CNN-based stock price prediction models, but few have leveraged hybrid architectures for MSM forecasting. Unlike prior models focusing on single deep learning approaches, this study provides empirical evidence that hybridization enhances financial forecasting. Compared to existing methods, our results confirm that integrating TCN and LSTM networks leads to more stable and accurate predictions, supporting the use of hybrid architectures in financial market analysis.

This study differentiates itself in three keyways:

- Model Fusion: Unlike previous research, this study implements a TCN-LSTM hybrid model, optimizing both short-term and long-term feature extraction.

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- Market-Specific Analysis: While prior studies focus on global markets (NYSE, NASDAQ), this research is one of the first to apply advanced deep learning techniques to MSM.
- Performance Evaluation: A rigorous comparative analysis of standalone TCN, LSTM, and the hybrid model, using MAE and RMSE, validates the effectiveness of model fusion.

4.4 Implications and Significance

The findings emphasize the importance of hybrid architectures in financial time-series forecasting, demonstrating that integrating convolutional and recurrent mechanisms leads to more accurate and reliable predictions. The hybrid TCN-LSTM model effectively balances short-term feature extraction with long-term memory retention, making it a robust choice for predicting stock market trends. These results align with previous studies highlighting the advantages of combining CNN-based architectures (such as TCN) with RNN-based models (such as LSTM) for improved time-series prediction. The hybrid approach is particularly beneficial for datasets with high temporal dependencies, such as financial markets, energy consumption forecasting, and weather prediction. These results demonstrate the effectiveness of hybrid deep learning models in financial forecasting, underscoring their potential applications in risk management, investment decision-making, and algorithmic trading.

4.5 Limitation and Future Work

The study has some limitations, including computational complexity, lack of adaptive hyperparameter tuning, and dependence on historical data without external macroeconomic factors. Addressing these issues in future research could improve model robustness. Future research directions should be more specific. Potential enhancements include:

- Implementing Bayesian Optimization or Grid Search for hyperparameter tuning.
- Exploring ensemble models combining multiple deep learning architectures for improved forecasting accuracy.
- Incorporating external financial indicators such as interest rates, inflation, and commodity prices to enhance model predictive power.
- Investigating the use of attention mechanisms to improve feature selection and weight distribution in hybrid models.

Applying transfer learning or reinforcement learning to adapt models to dynamic financial markets. This study contributes to financial forecasting research by introducing a hybrid TCN-LSTM model designed specifically for time-series stock market predictions. The model effectively combines the short-term pattern detection of TCN with the long-term memory retention of LSTM, making it a more well-rounded approach for weekly stock price forecasting. By proving the effectiveness of this hybrid TCN-LSTM model in financial forecasting, this study highlights how deep learning can improve decision-making in stock market investments and broader economic planning.

4.6 Gap from Prior Work

There are many previous studies that have focused on the application of deep learning models in the field of financial forecasting, especially those based on LSTM and CNN architectures. Although LSTM model can take into consideration long-term dependency of stock marketing data very well, but it does not perform well on short-term fluctuations. Meanwhile, TCN models rely upon causal dilated convolution for short-term pattern analysis, but they may not preserve long-term dependencies effectively. This study is distinct from previous studies by the following features:

Model fusion: Previous research typically utilizes a stand-alone model, whereas this paper develops a hybrid TCN-LSTM model that skillfully extracts short-term features while keeping long sequences intact. For example, TCN layers let us detect short-term fluctuations, while LSTM layers allow us to retain sequential memory.

This investigates application to MSM: Existing studies have been conducted on major global stock exchanges like NYSE, NASDAQ or NIFTY 50. Focusing on Muscat Securities Market which has yet to receive much attention in the literature, this research shed light on the unique features of a growing but underdeveloped market.

Performance evaluation: Unlike studies that either show the performance of single models, here we make a rigorous comparative analysis between the standalone TCN, standalone LSTM and the hybrid model. Evaluation metrics (MAE and RMSE) prove the efficiency of the hybrid approach.

Analytical Breakdown — Pros and Cons.

Pros: The hybrid model enhances prediction accuracy, reduces error margins, and effectively captures both short-time and long-time dependencies significantly.

Cons: The hybrid model has a higher computational complexity compared to standalone models, resulting in increased computational overhead that may extend training time and buck the requirement for more processing power especially when large-scale models are developed.

4.7 Discussion on Limitations

Despite its improved predictive capabilities, this study has certain limitations:

- Computational Complexity: The hybrid model requires higher processing power compared to standalone models.
- Lack of External Indicators: The model relies solely on historical stock data without integrating macroeconomic factors such as interest rates or inflation.
- Hyperparameter Sensitivity: Performance depends on the optimal tuning of learning rates and network depth.

While the hybrid TCN-LSTM model demonstrates significant improvements in predictive accuracy, its effectiveness is contingent upon model architecture and data availability. Future enhancements could involve leveraging ensemble techniques, external market indicators, and real-time adaptive learning to improve performance under volatile market conditions. Future research should explore ensemble learning approaches, integrate sentiment analysis, and apply transfer learning techniques to further refine forecasting accuracy.

5 CONCLUSION

This study investigated the effectiveness of TCN, LSTM, and a hybrid TCN-LSTM model in forecasting MSM stock prices. The findings confirmed that the hybrid model significantly outperformed standalone architectures, reducing prediction errors and enhancing market trend analysis. By integrating both short-term and long-term sequence learning, the hybrid model provides a more balanced and accurate forecasting approach. The superior predictive accuracy of the hybrid TCN-LSTM model validates the initial hypothesis that combining short-term convolutional feature extraction with long-term sequence retention enhances financial forecasting. These findings highlight the necessity of hybrid models in stock market prediction, offering significant improvements over traditional methods. These results reinforce the importance of hybrid deep learning techniques in financial modelling, with potential applications in risk management, investment strategies, and economic forecasting. Future enhancements could incorporate attention mechanisms, external financial indicators, and reinforcement learning methods to further optimize predictive performance.

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