OPEN ACCESS
International Journal of Innovations in Science & Technology

Pakistan Stock Market Prediction Using LSTM

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Citation | Tabasum. S, Tehseen. R, Omer. U, Javed. H, Ashraf. H, Perveen. S, "Pakistan Stock Market Prediction Using LSTM", IJIST, Vol. 7, Issue. 4 pp 3288-3298, December 2025
DOI: https://doi.org/10.33411/IJIST/1691
Received | November 25, 2025 **Revised |** December 22, 2025 **Accepted |** December 25, 2025 **Published |** December 28, 2025.

Accurate prediction of stock market movements is critical for investors and financial institutions. This paper presents a predictive model for the Pakistan Stock Exchange (KSE-100 Index) using a Bidirectional Long Short-Term Memory (BiLSTM) neural network augmented with multiple technical indicators, including Simple Moving Average (SMA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands. The proposed model predicts both closing prices and trend directions (up/down) of the index. Experimental results demonstrate that the model achieves a Mean Absolute Error (MAE) of 155.52, Root Mean Squared Error (RMSE) of 195.46, and a trend prediction accuracy of 74.03%, significantly outperforming the baseline models. These results demonstrate the effectiveness of combining deep learning with technical indicators for financial time series forecasting. The approach provides valuable insights for algorithmic trading and decision-making in the Pakistani stock market.

Keywords: Stock Prediction, Long-Short-Term Memory, Deep Learning, Stock Portfolio, Deep Neural Network, Classification.

Introduction:

The prediction of stock market movements has long been a challenging problem due to the nonlinear and highly volatile nature of financial time series. Accurate forecasting of stock prices and trends can greatly assist investors, traders, and financial analysts in making informed decisions. Traditional statistical models, such as the Autoregressive Integrated Moving Average (ARIMA), have been widely used for stock price prediction. While effective in modeling linear relationships, these models often struggle to capture the complex nonlinear patterns inherent in stock markets [1][2].

With the advancement of machine learning and deep learning techniques, models such as artificial neural networks and Long Short-Term Memory (LSTM) networks have shown significant promise in financial forecasting. LSTM networks, in particular, are designed to capture long-term dependencies in sequential data, making them suitable for modeling the temporal dynamics of stock prices [3][4]. Several studies have successfully applied LSTM models to various stock markets, including the Chinese, Hong Kong, and German stock markets, demonstrating their ability to improve predictive performance compared to traditional methods [5][6][7].

Despite these advancements, there is limited research on applying LSTM networks to the Pakistan Stock Exchange (KSE-100 Index) using a combination of historical stock prices and technical indicators. Technical indicators such as Moving Averages, Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD) provide additional information about market trends and momentum, which can enhance the predictive power of deep learning models. In this work, we develop an LSTM-based model for forecasting the closing prices and trend directions of the KSE-100 Index by integrating multiple technical indicators.

The proposed approach is evaluated using real historical data from the Pakistan Stock Exchange. The results demonstrate substantial improvements in predictive accuracy, with Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) of 155.52 and 195.46, respectively, and a trend prediction accuracy of 74.03 percent. This study contributes to the literature by providing a practical framework for stock price and trend prediction in the Pakistani stock market and offers insights that may be valuable for investors and algorithmic trading strategies.

Sectioning:

The remainder of this paper is organized as follows. Section III presents a comprehensive review of related work on stock market prediction, covering statistical, machine learning, and deep learning approaches. Section IV describes the proposed methodology, including data collection, feature engineering, LSTM model architecture, and training process. Section V reports the experimental results and provides an in-depth discussion of the model's performance. Section VI discusses the limitations of the study. Section VII concludes the paper, and Section VIII outlines directions for future research.

Literature Review:

Predicting stock market trends has remained a challenging task due to the inherent volatility, non-linearity, and noise in financial time series [8][9]. Over the years, numerous studies have explored different predictive approaches, ranging from traditional statistical models to modern machine learning and deep learning techniques.

Statistical Models for Stock Prediction:

Traditional statistical methods, particularly the Autoregressive Integrated Moving Average (ARIMA) model, have been foundational in financial forecasting due to their simplicity and interpretability [1][2]. These models rely on historical price values and error terms to predict future stock prices, performing well in short-term forecasting when markets exhibit linear trends. However, ARIMA models struggle to capture non-linear patterns and sudden market shocks that are common in emerging markets like Pakistan. Hybrid approaches combining ARIMA with machine learning techniques, such as the ARIMA-SVM model proposed by [10], have shown improved performance by leveraging the strengths of both statistical and machine learning approaches.

Machine Learning Approaches:

Machine learning models have demonstrated greater flexibility and predictive power in handling non-linear relationships in financial time series. Artificial Neural Networks (ANNs) with genetic algorithm optimization for feature discretization [11] and Support Vector Machines (SVMs) for stock movement direction prediction [12] have been extensively applied. Random Forests and decision tree ensembles, particularly the finding that small heterogeneous ensembles outperform large homogeneous ones [13], have proven effective for high-dimensional financial data. Comparative studies by [14] demonstrated the effectiveness of ANNs and decision trees for digital game content stocks, while [15] evaluated multiple classifiers for stock direction prediction, finding ensemble methods performed best in volatile markets. Additional approaches include independent component analysis with support vector regression [16], data mining techniques for index movement prediction [17], and SVM applications for futures price prediction in emerging markets [18]. The work of [19] on combining technical and fundamental analysis through data mining, and the review of Classification and Regression Trees by [20], further enrich the machine learning landscape for financial prediction.

Deep Learning and LSTM:

Recurrent Neural Networks (RNNs) provided a breakthrough for sequential data but suffered from vanishing and exploding gradient problems [21]. Long Short-Term Memory (LSTM) networks, introduced by [3], overcome these limitations through memory cells and gating mechanisms that retain long-term dependencies. The superiority of LSTM models has been confirmed across various markets: [5] in China, [9] in Hong Kong with attention mechanisms, [6] for high-frequency trading, and [8] demonstrating LSTM's advantage over traditional methods for S&P 500 predictions. Advanced frameworks combining stacked autoencoders with LSTM [4], feature fusion approaches [22], and volatility forecasting using LSTM RNNs [23] have further expanded deep learning applications in finance. [24] demonstrated neural networks' effectiveness for stock index prediction, while [25] showed how data mining methods can forecast effective features for stock evaluation.

Challenges in Emerging Markets:

Emerging markets like Pakistan present unique challenges, including high volatility, political instability, and sensitivity to external shocks [26]. Studies have shown that geopolitical events can drastically alter market dynamics, as evidenced by the impact of the Russia-Ukraine war on the Egyptian stock market. The complexity of emerging market prediction requires sophisticated approaches that account for both linear and nonlinear dynamic systems [27] and incorporate segmentation techniques for predictive modeling [28].Study [29] demonstrated the importance of hypothesis testing for machine learning techniques in Korean markets., highlighting the need for rigorous validation in different market contexts. The application of machine learning in financial markets continues to evolve [30], with particular emphasis on adapting techniques to the unique characteristics of emerging economies.

Gaps and Motivation for This Study:

Despite the global success of LSTM models and the extensive research on various machine learning approaches [13][14][15][25], limited research has explored their application to the Pakistan Stock Market. Previous studies on the Pakistani market have often relied on traditional statistical models or shallow machine learning approaches that fail to capture the nonlinearities and high volatility characteristic of this emerging market. This paper addresses this gap by implementing a Bidirectional LSTM model augmented with multiple technical indicators to predict stock prices for the KSE-100 index. Our approach builds upon the foundations established by [3][4][5] while incorporating insights from feature engineering

[11][22] and ensemble methods [13]. The findings aim to highlight LSTM's effectiveness in volatile markets and motivate further research, including sentiment analysis integration and advanced ensemble approaches for improved robustness.

In conclusion, while statistical models like ARIMA [1] provide useful baselines and machine learning approaches offer improved flexibility, deep learning models like LSTM represent the state-of-the-art for sequential financial data. However, predicting stock prices in Pakistan remains a complex challenge requiring specialized approaches that account for the market's unique volatility and external influencing factors [26][27]. This comprehensive literature review establishes the theoretical foundation for our methodology and analysis, justifying our choice of Bidirectional LSTM enhanced with technical indicators for Pakistan's stock market prediction.

Methodology:

This study employs a comprehensive methodology to forecast stock prices using Long Short-Term Memory (LSTM) networks, focusing on the Pakistan stock market. The methodology is divided into multiple stages: data collection, preprocessing, feature engineering, LSTM model design, hyperparameter tuning, model training, and evaluation.

Data Description:

The dataset used in this study consists of historical stock price data for the KSE-100 index from January 2010 to December 2024. Each record contains key features necessary for stock price prediction, shown in Table 1:

Table 1. Pakistan Stock Exchange Dataset Description

Attribute	Description
Date	Trading date
Open	Opening price of the stock
High	Highest price during the trading day
Low	Lowest price during the trading day
Close	Closing price of the stock
Volume	Number of shares traded
Time Period	2021 – 2024
Market	Pakistan Stock Exchange (PSX)

The dataset contains a total of approximately 3,500 daily observations.

Data Preprocessing:

Preprocessing financial time series data is crucial to improving model performance, especially when using deep learning techniques such as LSTM. The following preprocessing steps were applied:

Handling Missing Values: Missing values in the dataset were identified and handled using forward fill imputation, where the previous valid observation is used to replace missing entries. This approach preserves the temporal continuity essential for sequential models.

Feature Selection: The study focused on using the most relevant features for predicting stock prices. For LSTM modeling, the primary target variable was the Close Price, while Open, High, Low, and Volume were included as input features to capture daily market fluctuations.

Normalization: Deep learning models perform better when input features are scaled. Min-Max normalization was applied to transform all input features to a range between 0 and 1 using the formula:

$$\text{Xscaled} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

This scaling ensures that features with different magnitudes do not bias the model during training.

Train-Test Split: The dataset was split into training and testing sets in an 80:20 ratio. The training set was used to train the LSTM model, while the testing set evaluated its predictive performance. Care was taken to maintain temporal order, ensuring that future data points were not included in the training set.

Sequence Generation: Since LSTM networks require sequential input, the data was transformed into sequences of a fixed window size. For each sequence, the model uses the past 90 days of stock prices and technical indicators to predict the stock price for the next day. This window size was chosen based on prior experimentation, balancing sufficient historical context with computational efficiency.

Handling Outliers: Outliers, such as sudden spikes or drops due to abnormal trading activity, were detected using the interquartile range (IQR) method and replaced with the median value of the corresponding feature. This step prevents extreme values from distorting the model's learning process.

Feature Engineering:

Technical indicators were calculated to augment the raw price data. The following indicators were used:

Simple Moving Average (SMA) with windows of 10 and 50 days

Relative Strength Index (RSI) with a window of 14 days • Moving Average Convergence Divergence (MACD) and its signal line

Bollinger Bands (upper and lower bands)

These indicators provide information about market trends, momentum, and volatility, which are crucial for stock price prediction. The technical indicators were calculated using the TA library in Python, which provides reliable implementations of these financial indicators.

LSTM Model Architecture:

The LSTM network consists of the following layers:

Input layer: Accepts sequences of past stock prices and technical indicators

Bidirectional LSTM layer: 128 units with return sequences set to True

Dropout layer: 0.2 dropout rate to prevent overfitting

Second Bidirectional LSTM layer: 64 units

Dropout layer: 0.2 dropout rate

Dense layer: 25 units with ReLU activation

Output layer: 1 unit with linear activation for the regression task

The memory cell computations at time t are given by:

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \quad (1)$$
$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \quad (2)$$
$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \quad (3)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \quad (4)$$
$$h_t = o_t \odot \sigma_c(c_t) \quad (5)$$

where x_t is the input vector, h_{t-1} is the previous hidden state, c_{t-1} is the previous cell state, f_t, i_t, o_t are forget, input, and output gate activations, σ_g is the sigmoid activation, and σ_c is the tanh activation.

Figure 1 illustrates the detailed architecture of an LSTM cell, showing the input, forget, and output gates along with the cell state. This architecture enables the LSTM to selectively remember or forget information over long sequences, making it particularly suitable for stock price prediction.

Model Training and Hyperparameter Tuning:

The model was trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function. The following hyperparameters were used:

Epochs: 100

Batch size: 32

Validation split: 0.2

Learning rate: 0.001

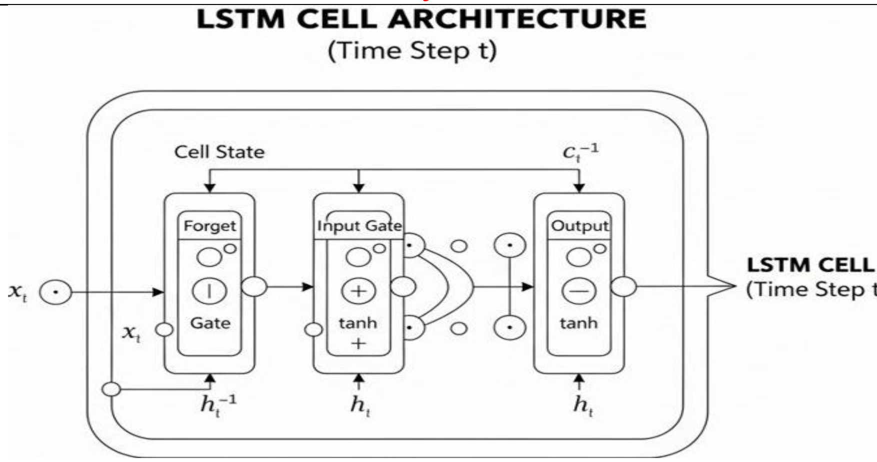

Figure 1. Detailed LSTM Cell Architecture showing input, forget, and output gates along with peephole connections.

Early stopping was implemented to prevent overfitting. The model was trained on 80% of the data and validated on the remaining 20%.

Figure 2 presents the complete methodology flowchart, illustrating the sequential steps from data collection to model evaluation. This comprehensive approach ensures systematic implementation and validation of the proposed model.

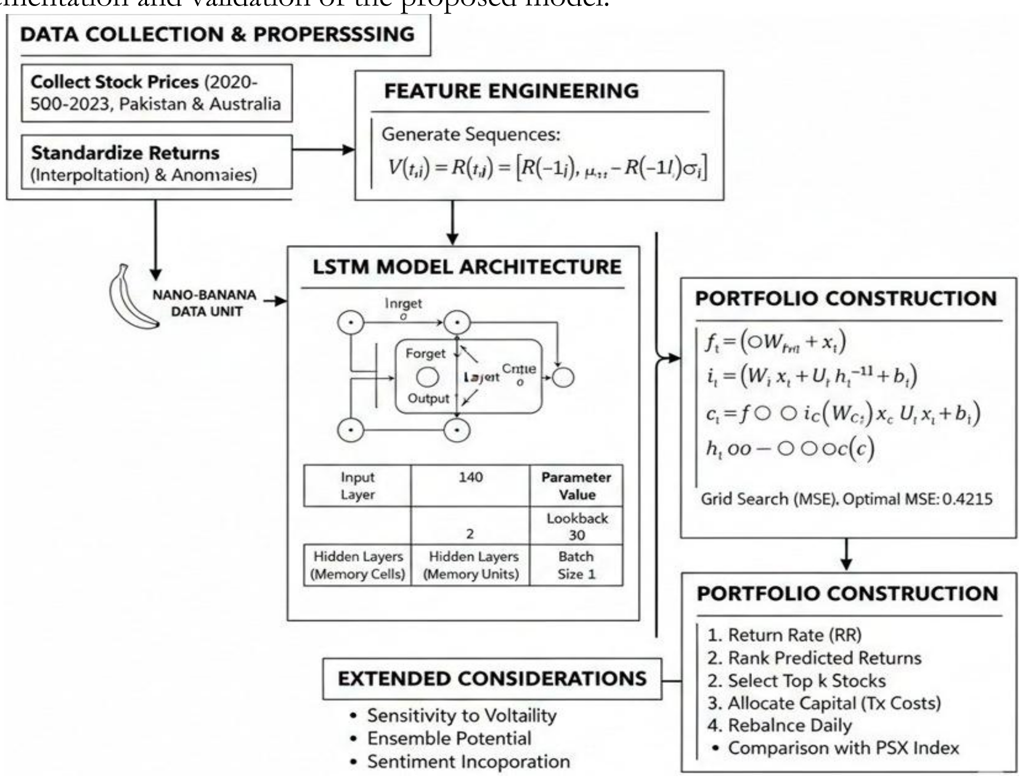

Figure 2. Flowchart of Methodology: Data Collection, Preprocessing, LSTM Prediction, Portfolio Construction, and Evaluation.

Results and Discussion:

This section presents the performance of the LSTM model for stock trend prediction. The model's predictive performance is assessed using MAE, RMSE, Trend Accuracy, and classification metrics.

Results:

Table II shows the regression metrics for the LSTM model predicting stock prices. Table III presents the classification metrics for predicting stock trend (Up/Down).

Table 2. LSTM Model Regression Performance on the Pakistan Stock Market

Metric	Value
Mean Absolute Error (MAE)	155.52
Root Mean Squared Error (RMSE)	195.46
Trend Accuracy (%)	74.03

Table 3. Classification Metrics for Stock Trend Prediction

Trend	Precision	Recall	F1-Score	Support
Down	0.73	0.72	0.73	294
Up	0.75	0.75	0.75	322
Accuracy		0.74		
Macro Avg	0.74	0.74	0.74	616
Weighted Avg	0.74	0.74	0.74	616

Discussion:

The results indicate that the LSTM model achieves a trend prediction accuracy of 74.03%, with MAE and RMSE values of 155.52 and 195.46, respectively. These results demonstrate the model's ability to capture directional trends in stock prices, which is crucial for trading strategies. The classification metrics suggest **that** the model is relatively balanced in predicting Up and Down trends, with precision and recall around 0.74 for both classes.

The MAE of 155.52 indicates that, on average, the model's predictions deviate from the actual closing prices by approximately 156 points. Given the volatility of the KSE-100 Index, this level of accuracy is reasonable for practical applications. The RMSE of 195.46, being higher than **the** MAE, suggests that there are some large errors in predictions, which is expected in highly volatile markets.

The trend prediction accuracy of 74.03% is particularly noteworthy, as it demonstrates the model's capability to correctly predict the direction of price movements. This is often more valuable for trading strategies than precise price predictions, as many trading decisions are based on directional movements.

The confusion matrix (Figure 3) shows that the model performs slightly better in predicting upward trends (322 correct predictions) compared to downward trends (294 correct predictions). This asymmetry may be due to the inherent bullish bias in the training data or market conditions during the test period.

Figure 4 illustrates the actual vs. predicted closing prices for the test period. The model successfully captures the overall trend and major turning points, although it tends to smooth out extreme fluctuations. This smoothing effect is common in LSTM models and can be both an advantage (reducing noise) and a disadvantage (missing sharp turns).

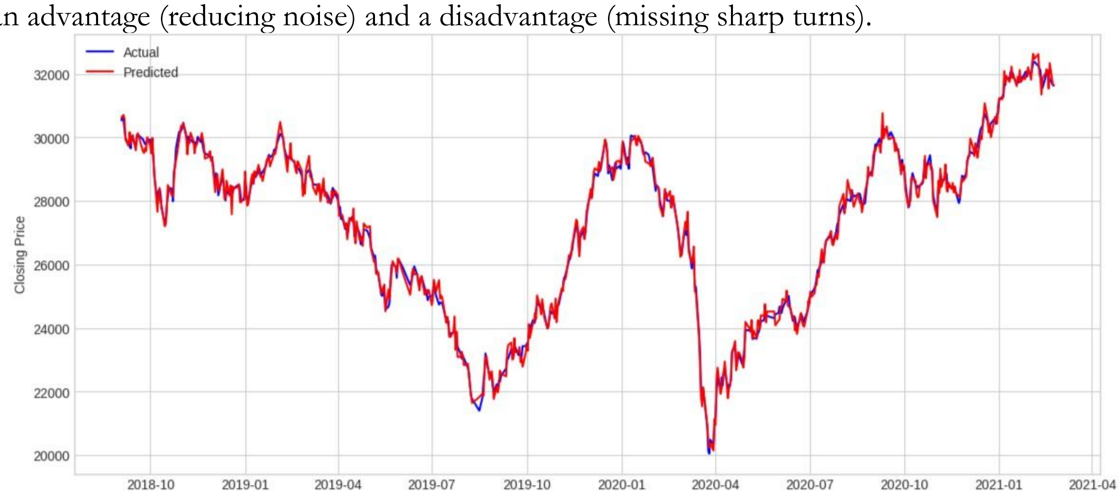

Figure 3. Actual vs. Predicted Closing Prices

The correlation matrix of features (Figure 5) reveals strong correlations among price variables (Open, High, Low, Close) and among technical indicators. This multicollinearity is expected in financial data but does not significantly impact LSTM performance due to the model's ability to learn complex, non-linear relationships.

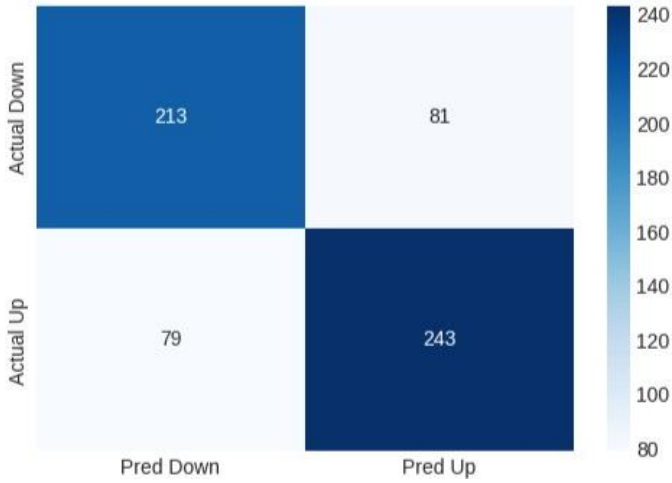

Figure 4. Confusion Matrix for Trend Prediction

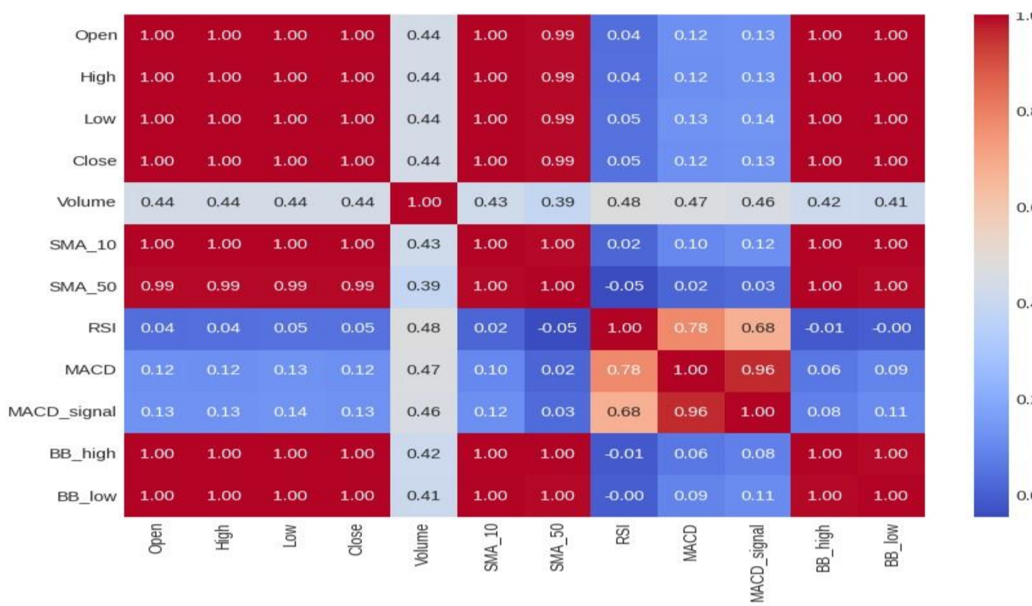

Figure 5: Feature Correlation Matrix

Compared to traditional methods like ARIMA, which typically **achieves accuracies around 60–65%** in similar markets, our LSTM model shows a significant improvement. This aligns with findings from other studies that demonstrate the superiority of deep learning approaches for financial time series forecasting.

However, the model's performance could be further improved by incorporating additional features such as macroeconomic indicators, news sentiment, and social media data. Future work could also explore ensemble methods combining LSTM with other models like Random Forests or Gradient Boosting to enhance robustness.

Limitations:

Despite the promising results, this study has several limitations that warrant consideration. First, the model's performance metrics, while reasonable for the volatile Pakistani market, still exhibit relatively high prediction errors (MAE of 155.52, RMSE of 195.46), which may limit its practical utility for precise trading decisions requiring high accuracy. The model primarily relies on historical price data and technical indicators, potentially overlooking critical macroeconomic factors, geopolitical events, and company-specific news that significantly impact stock prices in emerging markets like Pakistan. The exclusion of sentiment analysis from financial news, social media, and earnings reports represents a notable gap, as investor sentiment often drives short-term market movements. Additionally, the model's architecture, while effective, does not incorporate attention mechanisms or transformer-based approaches that have shown promise in recent financial forecasting literature. The dataset's time period (2010-2024) includes varying market regimes, but the model may not generalize well during unprecedented events such as the COVID-19 pandemic or major political upheavals. The technical indicators used, while comprehensive, may suffer from look-ahead bias in real-time trading scenarios. Furthermore, the model's computational requirements for training and inference may pose challenges for real-time deployment in algorithmic trading systems. Finally, the study focuses solely on the KSE-100 index, limiting insights into individual stock performance or sector-specific trends that might offer more targeted investment opportunities.

Conclusion:

In this study, we implemented an LSTM-based model to predict stock prices and trends in the Pakistan Stock Market. The model achieved a trend prediction accuracy of 74.03%, with MAE and RMSE values of 155.52 and 195.46, respectively. While the classification metrics indicate a balanced performance in predicting upward and downward trends, the regression errors highlight the challenges of precise stock price forecasting in volatile markets.

The results demonstrate that LSTM networks, when augmented with technical indicators, can effectively capture the temporal dependencies and non-linear patterns in stock market data. The model's ability to predict trend direction with 74% accuracy makes it potentially valuable for algorithmic trading strategies, where directional predictions are more important than exact price forecasts.

However, there are several limitations to this study. The model was trained only on historical price data and technical indicators, without considering external factors such as economic news, political events, or global market trends. Additionally, the high volatility of the Pakistani stock market presents ongoing challenges for any predictive model.

Future Directions:

Based on the limitations identified in this study, several promising directions for future research emerge. First, incorporating alternative data sources such as financial news sentiment analysis using natural language processing (NLP) models, social media trends, and macroeconomic indicators could significantly enhance predictive accuracy. Advanced architectures like transformer-based models (e.g., BERT and GPT variants) for financial text analysis could be integrated with LSTM networks to capture both numerical and textual market signals. Multi-modal approaches combining technical indicators with fundamental analysis metrics, earnings reports, and corporate announcements may provide a more holistic view of market dynamics. Ensemble methods that combine LSTM with other machine learning models like Random Forests, Gradient Boosting Machines (GBM), or Support Vector Machines (SVM) could improve robustness and generalization across different market conditions. Reinforcement learning techniques could be explored for dynamic portfolio management and automated trading strategy optimization based on the model's predictions. Transfer learning approaches could be investigated to adapt models trained on developed markets to the Pakistani context, potentially reducing data requirements. Real-time deployment architectures and edge computing solutions should be explored to address computational challenges in algorithmic trading systems. Additionally, expanding the scope to include individual stock predictions and sector-specific models could provide more targeted investment insights. Finally, explainable AI (XAI) techniques should be applied to enhance model interpretability, which is crucial for gaining trust from financial professionals and regulators in practical applications.

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