

Stock Price Prediction Model: Assessing the Performance of a Hybrid Deep Learning Model Employing Multi-Stream Data

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ABSTRACT

Purpose - The study investigates the effectiveness of the ConvLSTM model in the next-day closing price prediction for stocks using a novel combination of input features. These features include past prices, prices of related stocks, technical indicators of the target stock, mutation point impact on closing price, stock market sentiment, stock market index, interest rate, and dollar exchange rate

Study Design/Methodology/Approach - Sentiment analysis of financial news related to the Pakistan Stock Exchange (PSX) was performed using the pre-trained FinBERT model. Relevant stocks were identified through historical prices using Random Forests and XGBoost algorithms. A comparative analysis was conducted involving ConvLSTM1D and ConvLSTM2D models, as well as LSTM, CNN, and CNN+LSTM models, all having the same network structure.

Findings - The study found that there is not a universal best model for every stock. However, the ConvLSTM1D model exhibited the best average performance for Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) across the selected stocks.

Practical Implications - The findings suggest that while no single model is optimal for all stocks, the ConvLSTM1D model may be particularly effective for improving prediction accuracy in stock closing prices. This can aid investors and analysts in making more informed decisions based on the model's performance metrics.

Originality/Novelty - This study provides a novel approach by integrating a diverse set of input features and comparing multiple models in a comprehensive manner. The use of sentiment analysis and advanced machine learning techniques such as ConvLSTM adds significant value to the field of stock price prediction.

Keywords: Stock Price Prediction, ConvLSTM, Random Forests, XG Boost, Pre-trained FinBERT, Mutation Points, LSTM, CNN

1 | INTRODUCTION

Stock represents a share in business ownership and its market price is determined by supply and demand factors. As stock trading entails both high risks and high rewards, there is a need for precise price forecasting of stocks so that investors, fund owners, and financial managers may vary their plans accordingly. However, the dynamic and non-linear nature of stock markets makes the task of stock price prediction daunting (Park et

al., 2022). Traditionally, investors employed technical along with fundamental analysis based on historic stock price data for forecasting and prediction (Jing et al., 2021). Autoregressive models (AR) along with their related extensions are amongst the earlier models for stock price prediction (Adebiyi et al., 2014). Most of the previous models were based on time series (Yan & Guosheng, 2015). The prediction accuracy of such models plateaued at an overall level because of the presence of non-stationarity and seasonality in time series data. Therefore, researchers focused their attention on machine learning models like Support Vector Machines and Random Forests (Das et al., 2022). However, these algorithms were not able to effectively handle high-dimensional complex stock market data. Consequently, deep learning models were developed that were adept at dealing with time series data (Jiang, 2021). Long-short-term memory (LSTM) and convolutional neural networks (CNN) are among the successful deep learning models currently being employed (Tashiro et al., 2019). Therefore, an adaptation of CNN has been employed in this research.

2 | LITERATURE REVIEW

The related work reveals that significant research has been conducted to combine stock prices with sentiment analysis for forecasting (Long et al., 2020). However, the incorporation of mutation points and the effect of related stocks remains underexplored. Furthermore, a combination of historic stock prices, mutation point data, related stocks, target stock financial indicators, macroeconomic indicators such as market index, interest rate, and dollar rate, and sentiment analysis of financial news as input features have not yet been investigated. A country's stock market and the prevailing macroeconomic conditions are interlinked. Various fiscal parameters such as interest rates and dollar exchange rates affect the share market in one way or another. Another study employed regression analysis to investigate the relationship between policy rate and stock price (Zhou, 1997). The results revealed that interest rates had a major impact on stock returns, particularly over long periods. In 1997, Lee adopted a rolling regression methodology to examine the relationship between the equity market and shorter-term interest rate in a bid to predict the excess returns of especially S&P 500 stock market i.e. the difference between the return provided by the stock market and the risk-free interest rate provided by treasury bond. The authors analyzed data from 15 different countries to study the empirical relationship between stock prices and monetary policy rates (Alam & Uddin, 2009). They uncovered a significant negative association between share prices and the prevailing interest rate. A study was focused on the prediction potential of dollar rate fluctuations in Pakistan on the country's stock market. The study showed that the best prediction results using dollar exchange rate and past prices as input features are provided by Random Forest and Decision Tree algorithms (Saeed & Jamil, 2022). Therefore, to capture the macroeconomic environment of the country, this research also proposes the inclusion of the dollar exchange rate, policy interest rate, and stock market index along with market sentiment as input features.

Despite the advancement in prediction algorithms being employed, the prediction potential of interrelationships among stocks largely remained unexplored. This potential was proved by Nam & Seong in 2019 when they predicted stock prices of the Korean Stock Market (Nam & Seong, 2019). Later on, another study employed knowledge graphs and deep learning models for stock price prediction, concentrating on connected stocks and mutation points (Tao et al., 2022). In the particular study, the authors assess the influence of the intended stock and linked businesses on the potential stock price and give weightage to different

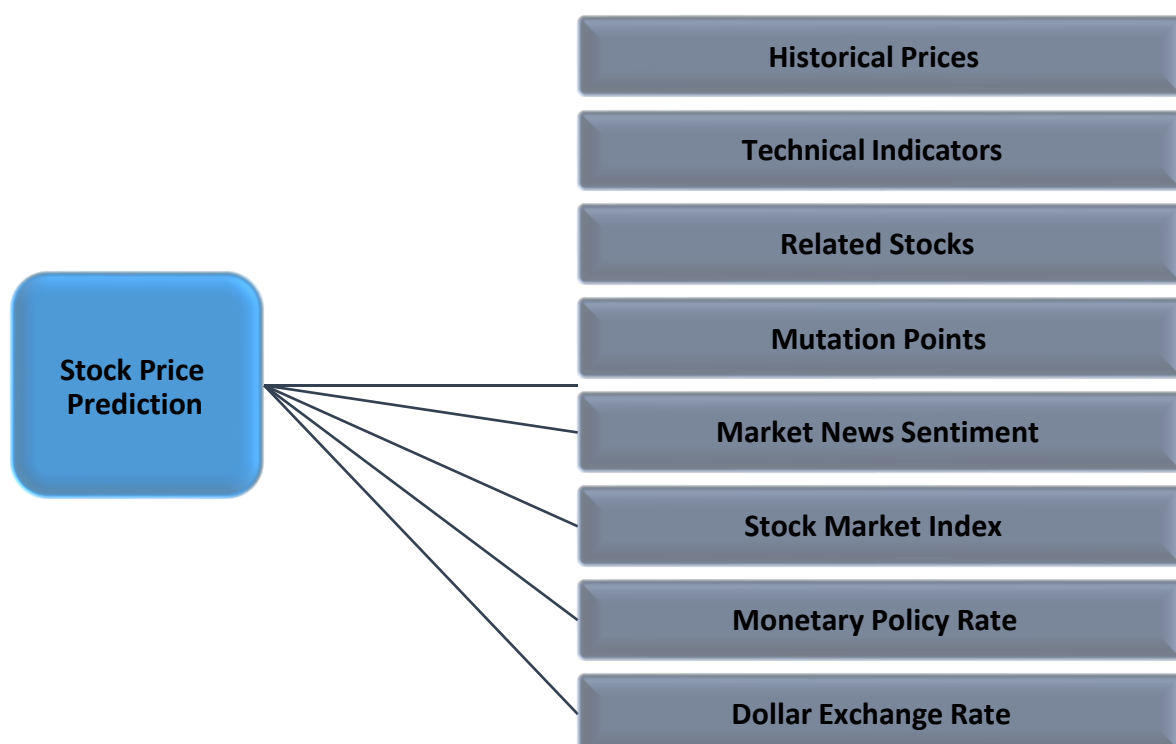
securities based on the level of correlation. Their results showed improved price prediction performance after the incorporation of correlated stock data with past prices.

According to several studies, financial news has an impact on how the share price will behave in the future (Shah et al., 2022). Users will buy or trade the shares after reading a published article or an online post even if the views are not technically correct. This behavior will cause investors to buy a sizable amount of shares, which will cause the trend to shift either higher or downward. Recent results from the pre-trained language models have shown that such models can generate exceptional results for all subsequent language processing tasks including sentiment assessment. Researchers were able to train a self-supervised model from a vast text corpus to understand the basic information that could be shared and aid many other NLP activities owing to the enhanced computational resources and vast amounts of textual data available on the web (Cheng et al., 2022).

Previously a price prediction model was developed to incorporate knowledge graphs and deep learning with a stock price forecasting neural network that included connected stocks and mutation points (Tao et al., 2022). ConvLSTM model network has been adopted from the mentioned study. Market technical indicators, macroeconomic indicators, and market financial news sentiment were not part of the above-stated model. This research includes these features in the stock price prediction input list along with historic market prices, past prices of related stocks, and disruption (mutation) data points.

Figure 1

Stock price prediction input list



3 | METHODOLOGY & DESIGN

The proposed research is a quantitative correlational study that focuses on forecasting target prices using quantitative data. Even though the impact of financial news is also included in the proposed model, the textual data has been converted into sentiment scores (quantitative data) for further processing. In this research, both random forests and the XG Boost model are used to find the top 10 most important features for target stock based on historical prices. The top 10 features highlighted by algorithms are then included in the final input list as related stocks.

This research used a pre-trained FinBERT model for sentiment analysis of financial news headlines and summaries available on the “HuggingFace” website. The model outperforms other BERT-based models in NLP applications (Yang et al., 2020). The model is trained specifically on a financial text corpus. The size of the training data is 4.9 billion tokens. Assessing the effectiveness of any forecasting model is critical because business actions are often based on results produced by these models. Performance metrics for the time series forecasting model offer an overview of the model's ability to make predictions. MSE, RMSE, and MAE have been used in this study to assess the effectiveness and accuracy of the prediction.

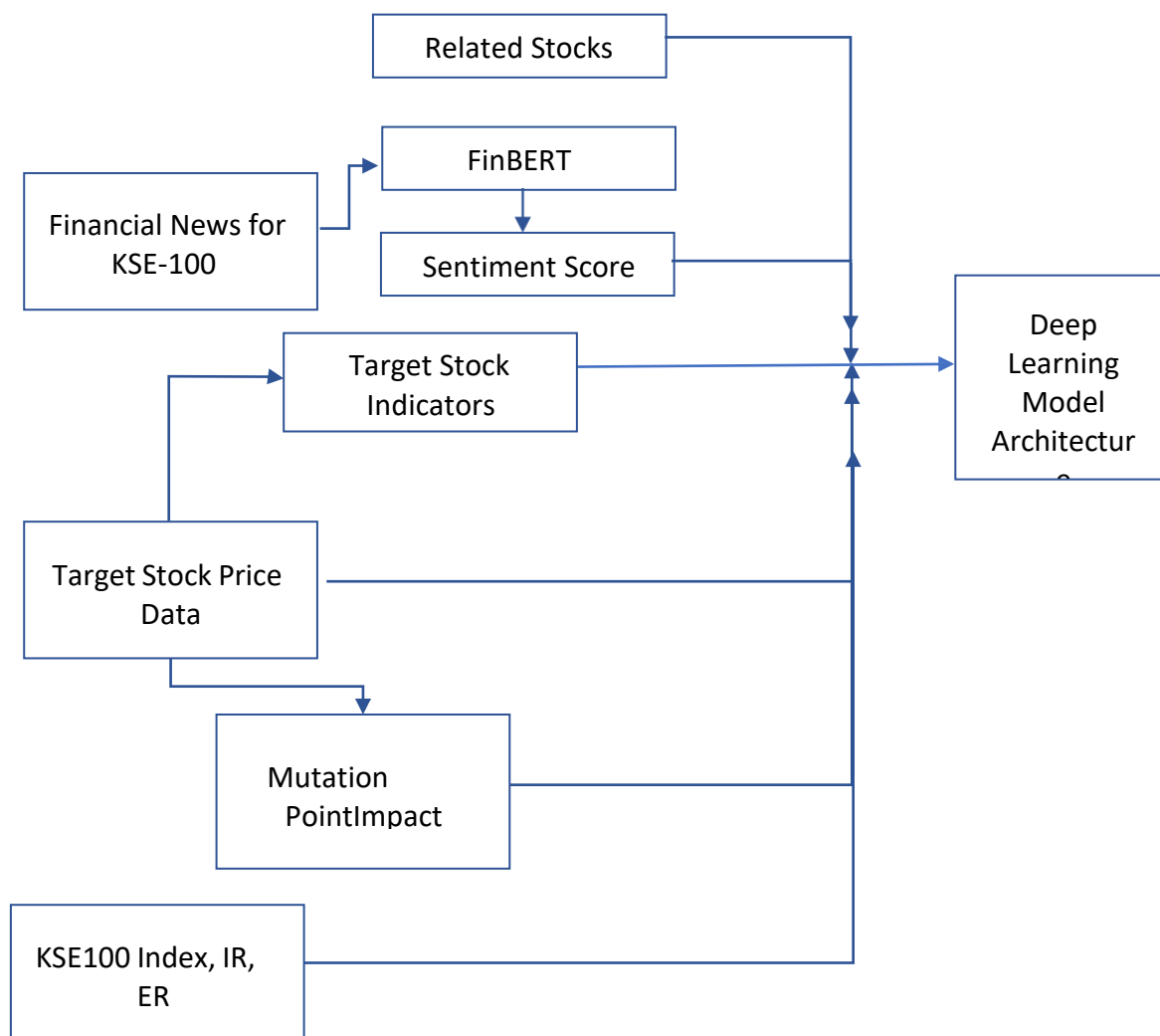
In deep learning, the loss function is a core construct that represents loss, risk, or cost associated with a random event by mapping positive real numbers to the event values (Kersting, 2018). Stock values are particularly nonlinear and volatile. Many external factors such as enterprise performance, macroeconomic environment, and national as well international events affect the prices. Many of the prevalent deep learning-based stock estimation algorithms employ the mean squared error (MSE) loss function which is an L2 loss function. It is differentiable throughout and converges quickly in gradient descent. Therefore, this study uses MSE as a loss function.

Training of neural networks is a stochastic process i.e., the initial assignment of weights to different nodes in different layers is random. Therefore, it is not uncommon that neural networks produce slightly different results during multiple runs on the same data with the same hyperparameters and model architecture. Considering the need for simulation as well as the constraint of available computational resources, this study has run each model 20 times and results against different training and test performance metrics are averaged out to report final results.

3.1 | Visual Framework of the Study

Figure 2

Research Methodology Structure



There are two variations of the proposed ConvLSTM model. ConvLSTM1D and ConvLSTM2D models. Besides the proposed model, LSTM, CNN, and CNN+LSTM models are also implemented based on the above framework and results compared.

3.2 | Network Architectures for Deep Learning Networks

Figure 3

LSTM Network Architecture

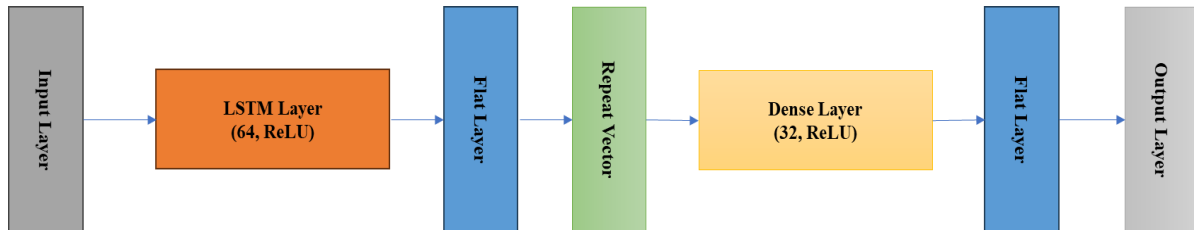


Figure 4

Network Architecture for CNN Network

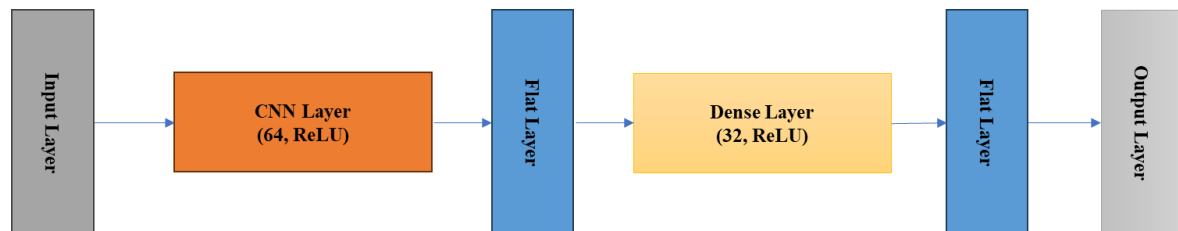


Figure 5

Network Architecture for CNN + LSTM Network

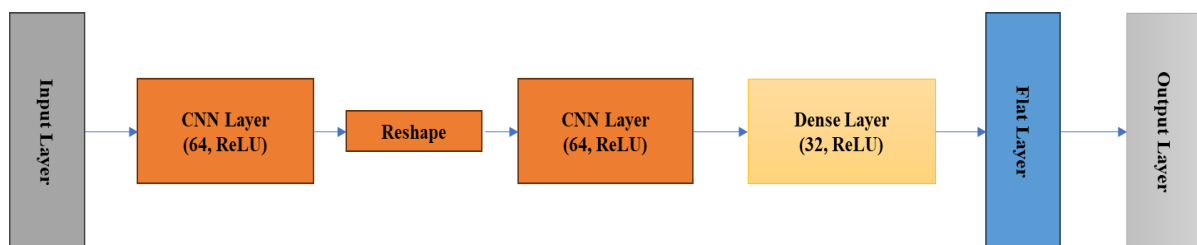
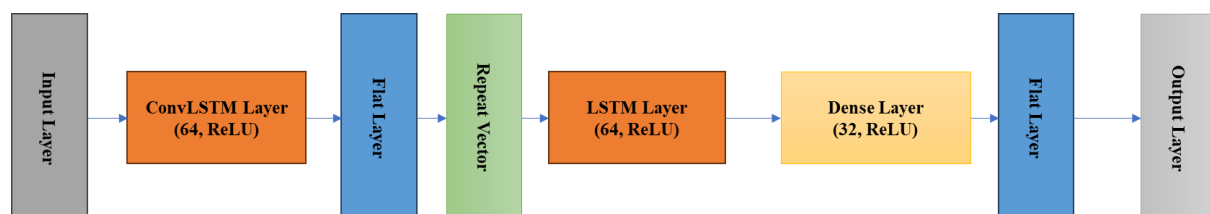


Figure 6

Network Architecture for ConvLSTM Network



4 | RESULTS and ANALYSIS

For the selection of stocks for analysis, only the stocks for which the number of observations recorded equaled 100% of total trading days were filtered out. This resulted in a subset of 33 stocks to choose from. Considering sectors as well as average daily volume, the following 6 stocks were selected for further analysis and testing.

- ENGRO (Engro Corporation Limited)
- LOTCHEM (Lotte Chemical Pakistan Limited)
- NML (Nishat Mills Limited)
- TRG (TRG Pakistan Limited)
- HBL (Habib Bank Limited)
- KEL (K – Electric Limited)

Deep learning models are implemented using Python, Keras, and other auxiliary libraries. Kaggle servers have been used for model training and simulations. For model training, rolling window cross-validation is performed considering we have time series data. 80% of overall data is used for training purposes while 20% of data is reserved for model testing and validation. A 7-day window of each input feature is used for each model.

For identification of related stocks target stock using historical prices, random forests and XG Boost models were used. Since the focus of the research was on the identification of most stocks with the highest prediction potential for a given stock, therefore, model training was done using a complete dataset so that the model can effectively learn all the intricate and complex relations between different stocks. The top 10 related highlighted by each algorithm are combined to produce related stock feature subsets. There exists a considerable degree of overlap between the results produced by both ensemble learners. While the degree of overlap varies, there is no instance in which both models produced completely different results. The difference between selected features is grounded in the difference in approach through which both models select features. While random forest selection features are based on the increase in prediction error encountered by feature shifting, the XG Boost model calculates feature importance using the “Gain” metric. The results of feature selection for each target stock obtained are shown below.

Figure 7

Related Stocks Selection for KEL

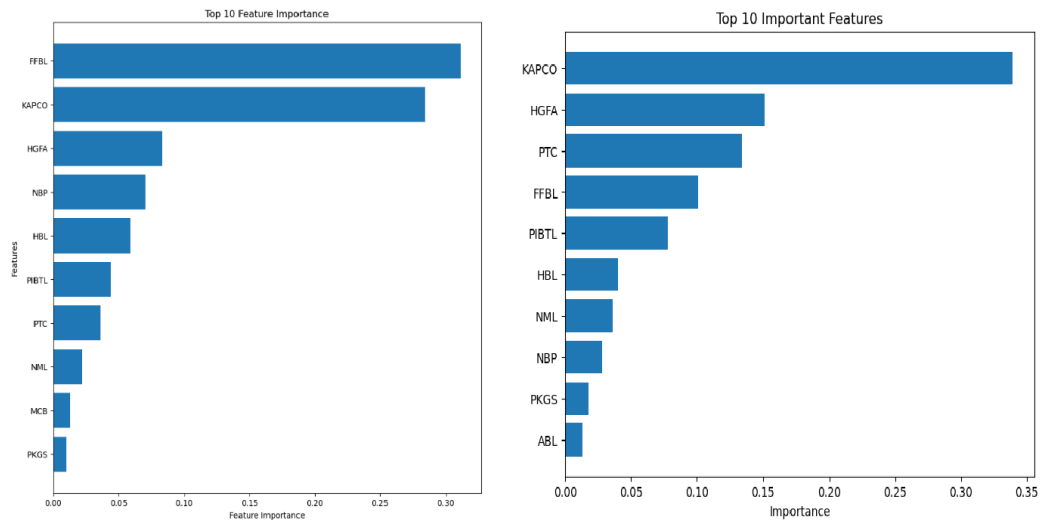
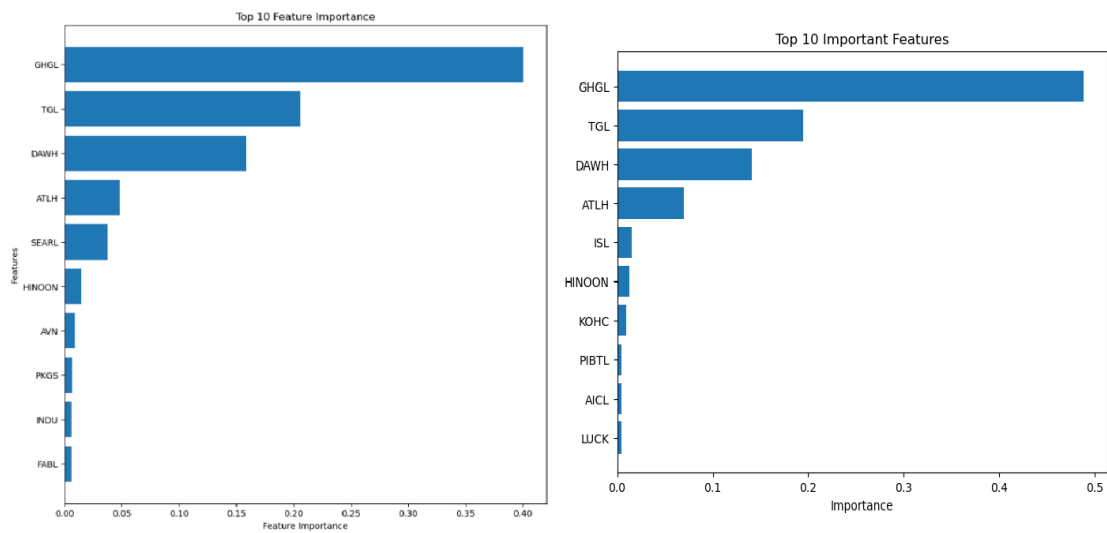
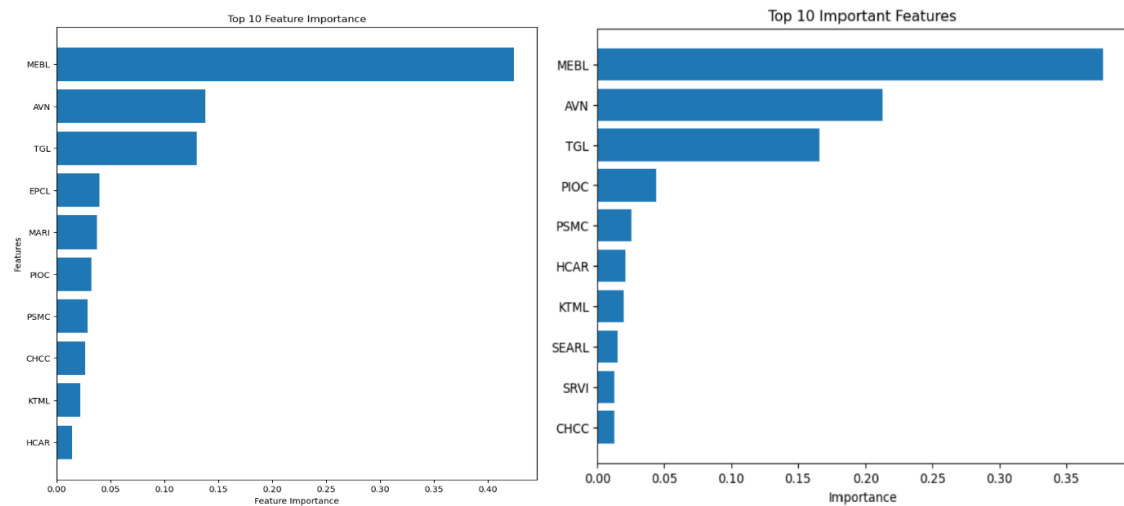
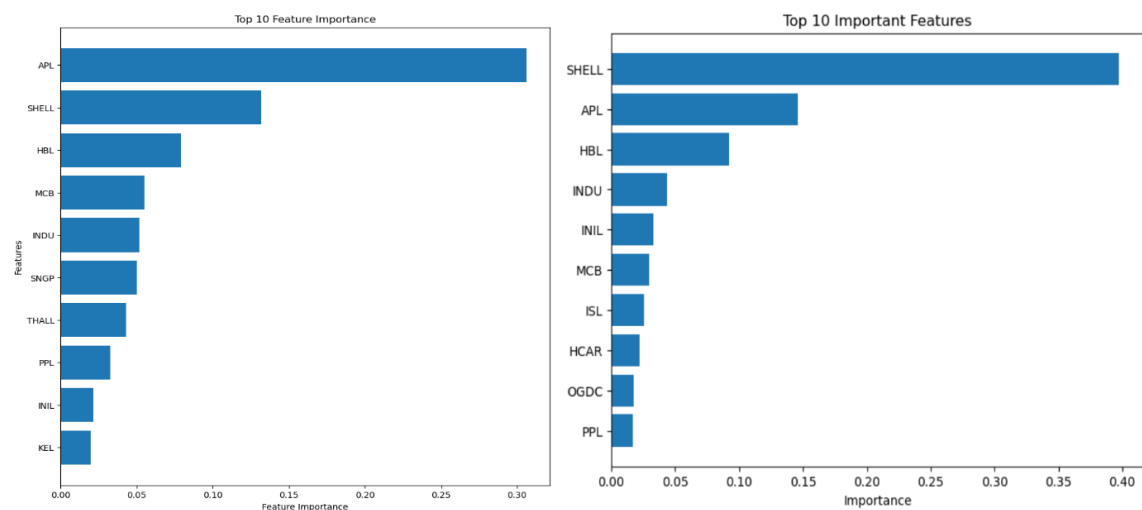
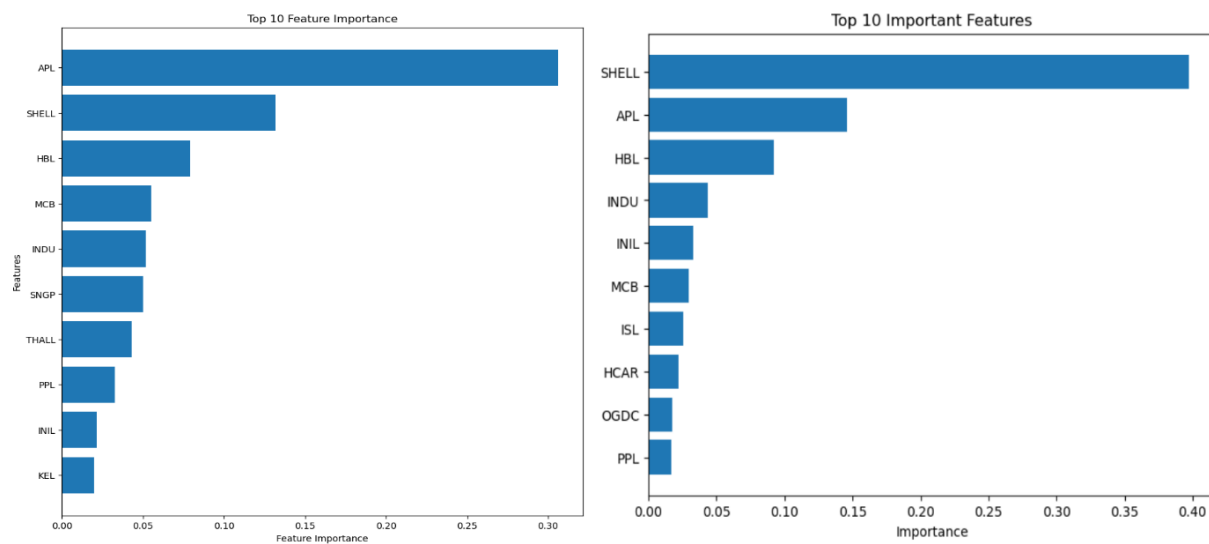
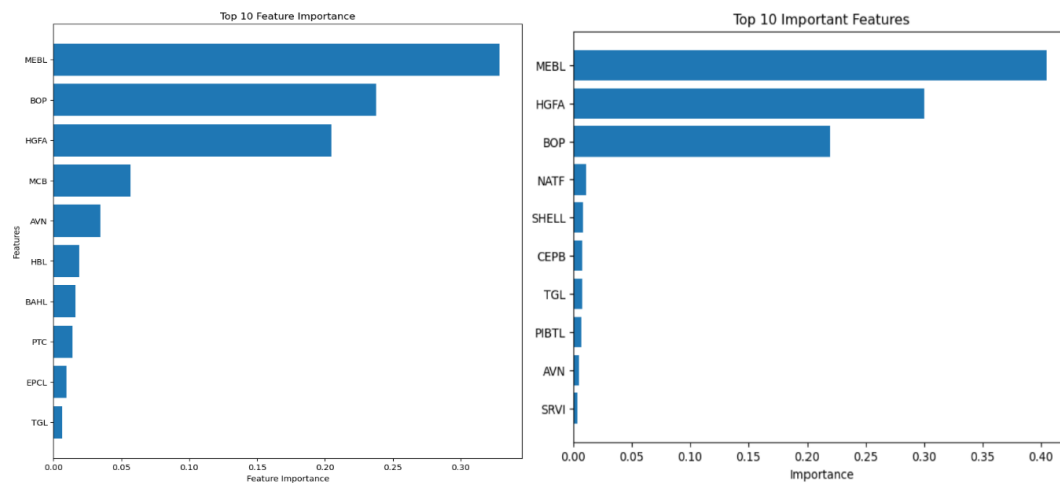
**Figure 8***Related Stocks Selection for ENGRO***Figure 9***Related Stock Selection for HBL*

Figure 10*Related Stock Selection for TRG***Figure 11***Related Stocks for NML***Figure 12***Related Stocks for LOTCHEM*

4.1 | Sentiment Analysis Results Using FinBERT

As a result of web scrapping, 888 articles related to KSE-100 and PSX were found in the archives of Business Recorder. The number of articles of concern found from archives from Dawn News was 151 whereas 117 articles were found from scrapping the Pkrevenue website. Hence, a total of 1156 articles were found for which news headline and summary excerpt data was collected. A glimpse of the sentiment analysis results of the FinBERT model is shown below.

Table 1

Sentiment Analysis Results Using FinBERT Model

Neutral	Positive	Negative	News text	Date
0.035	0.000	0.965	KSE mid-day update. On Wednesday, until mid-day, the KSE-100 Index was at 16534.93 with a negative change of 259.94	2013-01-02
0.014	0.986	0.000	KSE mid-day update. On Thursday, until mid-day, the KSE-100 Index was at 16542.38 with a positive change of 52.39	2013-01-03
0.028	0.972	0.000	KSE mid-day update. On Thursday, until mid-day, the KSE-100 Index was at 16684.89 with a positive change of 96.35	2013-01-04
0.006	0.000	0.994	KSE mid-day update. On Monday, until mid-day, the KSE-100 Index was at 16473.64 with a negative change of 175.20	2013-01-07
0.010	0.990	0.000	KSE mid-day update. On Tuesday, until mid-day, the KSE-100 Index was at 16568.83 with a positive change of 66.18	2013-01-08
0.000	0.000	1.000	The Index loses 146.19 points. The Karachi stock market on Monday closed lower mainly due to ongoing political uncertainty and the benchmark KSE-100 index lost 146.19 points to close at 16,502.65 points from 16,648.84 points on Friday.	2013-01-08
0.002	0.998	0.000	KSE mid-day update. On Wednesday, until mid-day, the KSE-100 Index was at 16687.98 with a positive change of 42.22	2013-01-09
0.001	0.000	0.999	KSE mid-day update. On Thursday, until mid-day, the KSE-100 Index was at 16591.18 with a negative change of 151.04	2013-01-10
0.000	1.000	0.000	The bullish trend continues. For the second consecutive day on Wednesday, the Karachi Stock Exchange (KSE) witnessed a bullish trend and the benchmark KSE-100 index gained 96.46 points to close at 16,742.22 points from 16,645.76 points a day earlier.	2013-01-10

0.000	0.000	1.000	Index loses 212.3 points. Due to growing uncertainty on the political front, Karachi Stock Exchange (KSE) on Thursday witnessed a bearish trend and the benchmark KSE-100 index lost 212.3 points to close at 16,529.92 points from 16,742.22 a day earlier.	2013-01-11
0.000	1.000	0.000	Index gains 104.79 points. On the last trading day of the week on Friday, the Karachi Stock Exchange (KSE) witnessed a bullish trend till the end and the benchmark KSE-100 index gained 104.79 points to close at 16,634.71 points from 16,529.92 a day earlier.	2013-01-12
0.972	0.000	0.028	SC ordered the arrest of PM, the KSE 100 index lost 453.46 points. Supreme Court (SC) top judge on Tuesday ordered the arrest of the Prime Minister over alleged corruption	2013-01-15

It can be seen from the above results that news that contains information regarding financial affairs only is identified very accurately by the model. However, when financial news is merged with non-financial news in such a way that text related to financial matters is sparse, the performance of the model deteriorates. This trend which can be seen in the last data instance in Table 1 is observed throughout the dataset. However, the quantity of such data instances is very few in the data. Instead of passing categorical data to the deep learning models, these sentiment probabilities are passed as continuous input features.

4.2 | Next-Day Closing Price Prediction Performance

For each of the selected stocks analysis and testing, forecasting of the next day's closing price using 7 window days and 0% training data was carried out using LSTM, CNN, CNN+LSTM, ConvLSTM1D, and ConvLSTM2D network architectures. Rolling window cross-validation was carried out during the model training phase. For the evaluation of performance, three matrices were used: MSE, MAE, and RMSE. A simulation study for each model was carried out in which model training testing and evaluation were carried out 20 times and then the results were averaged.

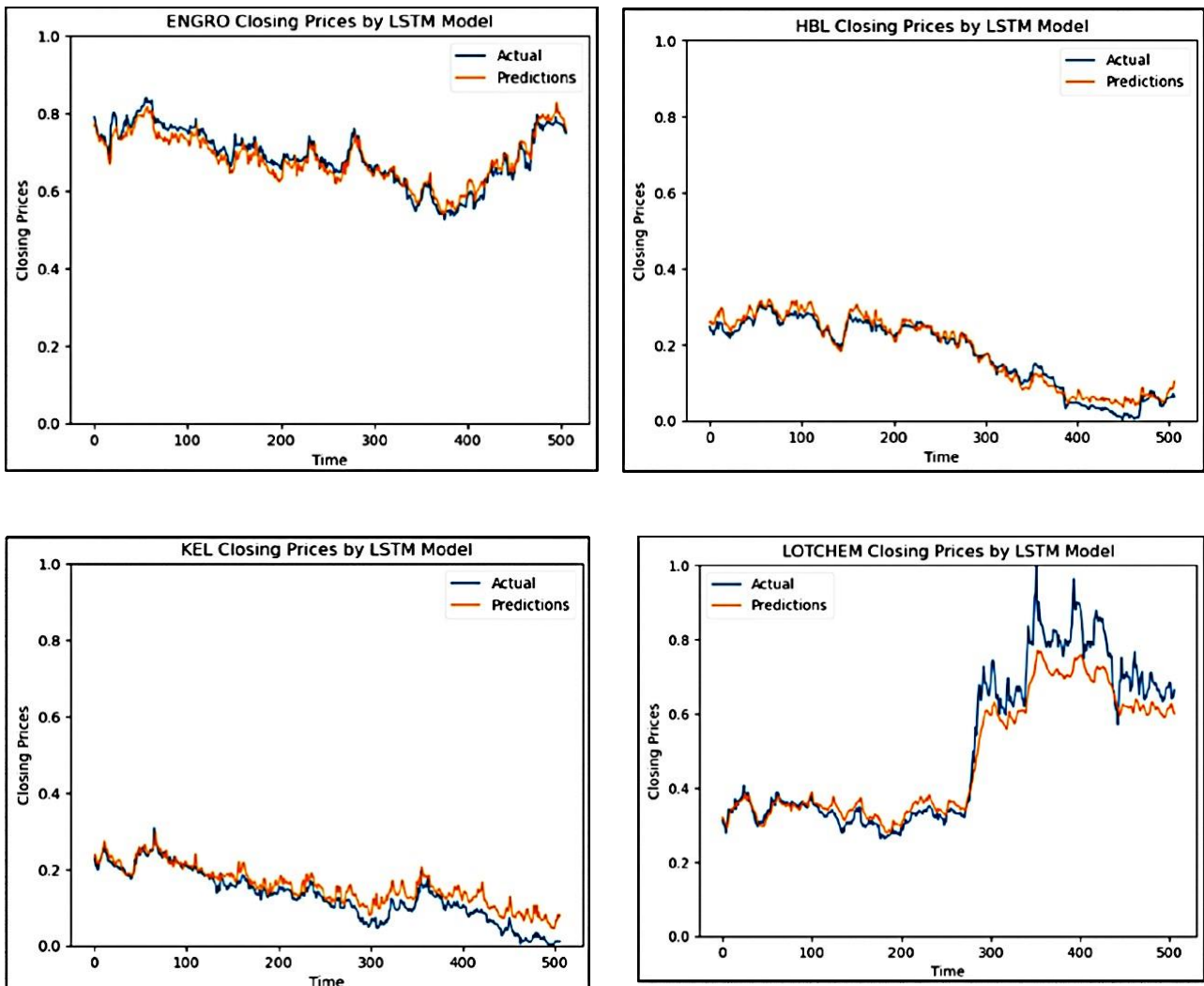
4.3 | Performance of LSTM Model for Price Prediction

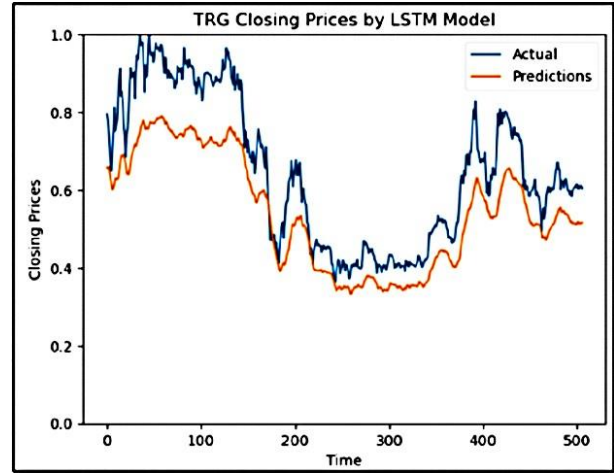
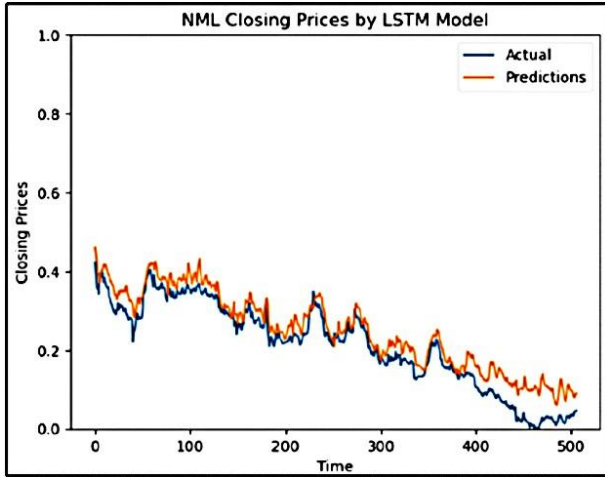
The results of training and testing evaluation of the LSTM model for each of the selected stocks are summarized in Table 2. It can be seen that the performance of LSTM is not consistent for all the stocks. LSTM gives the best performance for ENGRO and NML stocks while for TRG and LOTCHEM stocks, its performance deteriorates. Moreover, a perusal of training and testing error measures shows that the model is not overfitting to the data.

Table 2*LSTM Model Training and Testing Evaluation*

Stock	Model Training			Model Testing		
	Avg. MSE	Avg. MAE	Avg. RMSE	Avg. MSE	Avg. MAE	Avg. RMSE
ENGRO	0.00041	0.01518	0.02004	0.00078	0.02258	0.02749
HBL	0.00225	0.02166	0.02743	0.00737	0.05463	0.06085
KEL	0.00051	0.01718	0.02249	0.00181	0.03287	0.04017
LOTCHAM	0.00375	0.03140	0.03937	0.04823	0.12332	0.14758
NML	0.00054	0.01682	0.02326	0.00158	0.03126	0.03918
TRG	0.00120	0.01275	0.02826	0.03479	0.14571	0.16200
	0.00144	0.01917	0.02681	0.01576	0.06839	0.07954

The LSTM model has been able to capture the general direction of stock movement for all the stocks as depicted in the following lines graphs showing predicted and actual next-day closing prices.

Figure 13*Stock Closing Price Prediction Using LSTM Model*



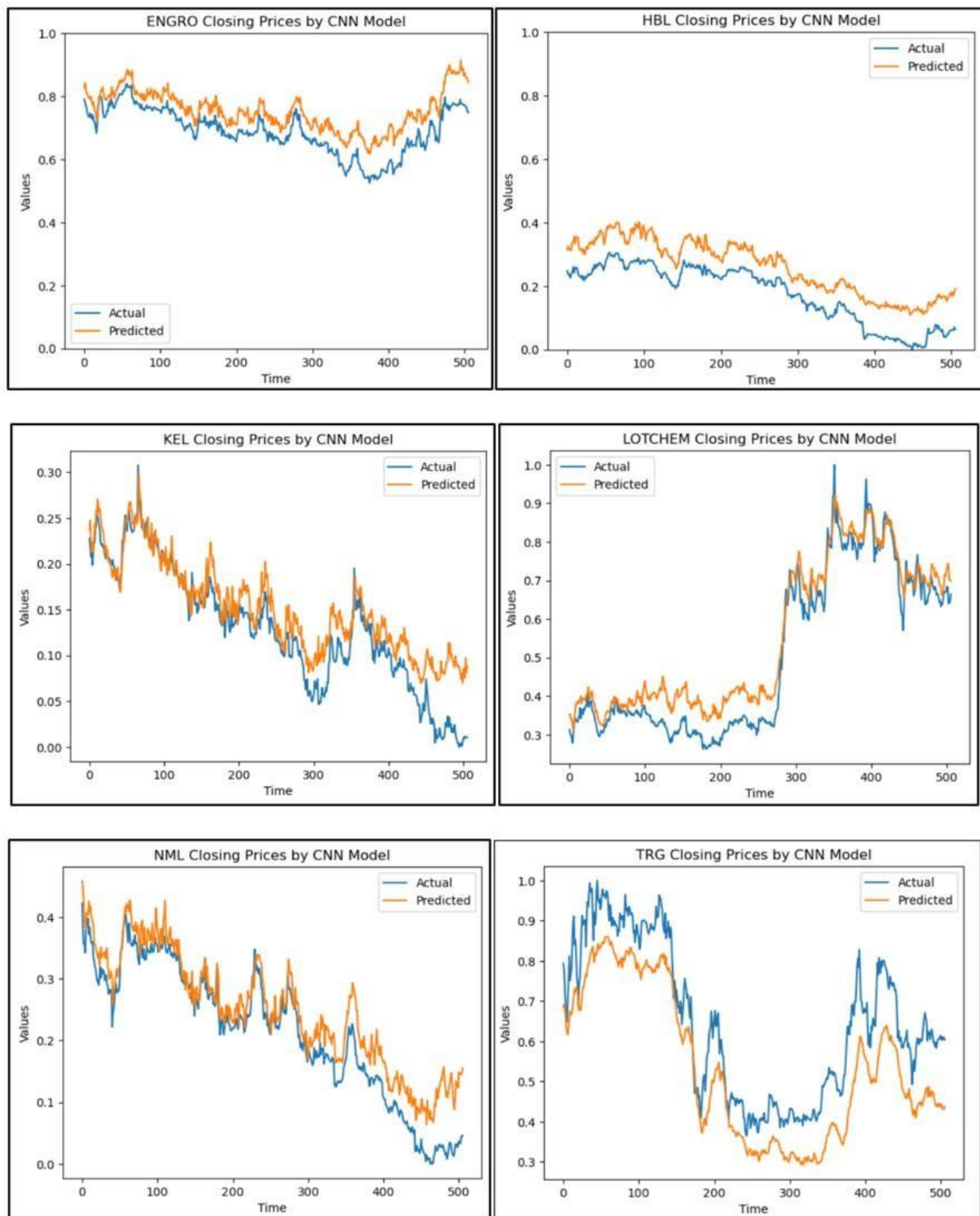
4.4 | Performance of CNN Model for Price Prediction

Table 3 presents the summary of model training and testing results obtained by employing the CNN (Conv2D) model for the task of next-day closing price prediction. Based on evaluation metrics, the CNN model gives the best results for KEL stock with testing MSE, MAE, and RMSE of 0.00116, 0.02691, and 0.03190 respectively. Except for TRG, the performance of the CNN model is consistent across all the stocks. The model can follow stock price fluctuations closely.

Table 3

CNN Model Training and Testing Evaluation

Stock	Model Training			Model Testing		
	Avg. MSE	Avg. MAE	Avg. RMSE	Avg. MSE	Avg. MAE	Avg. RMSE
ENGRO	0.00044	0.01557	0.02088	0.00584	0.06911	0.07508
HBL	0.00041	0.01445	0.02012	0.00422	0.06165	0.06400
KEL	0.00053	0.01737	0.02289	0.00116	0.02691	0.03190
LOTCEM	0.00018	0.00933	0.01323	0.00375	0.05147	0.06069
NML	0.00060	0.01837	0.02419	0.00219	0.03920	0.04492
TRG	0.00079	0.01146	0.02774	0.02774	0.15164	0.16333
	0.00049	0.01443	0.02151	0.00748	0.06666	0.07332

Figure 14*Closing Stock Price Prediction using CNN Model***4.5 | Performance of CNN + LSTM Model for Price Prediction**

The CNN+LSTM model comprises a CNN layer for capturing spatial interactions and a separate LSTM layer for configuring time sequences. So, this model combines the features of both CNN and LSTM models. This is the reason why model performance across all six stocks is fairly consistent. Like the CNN model, the

best results are achieved for KEL stock. The strength of this model is seen in the prediction of TRG as the CNN+LSTM model achieved almost 50% reduction in each of the three error metrics. A summary of the results is shown in Table 4.

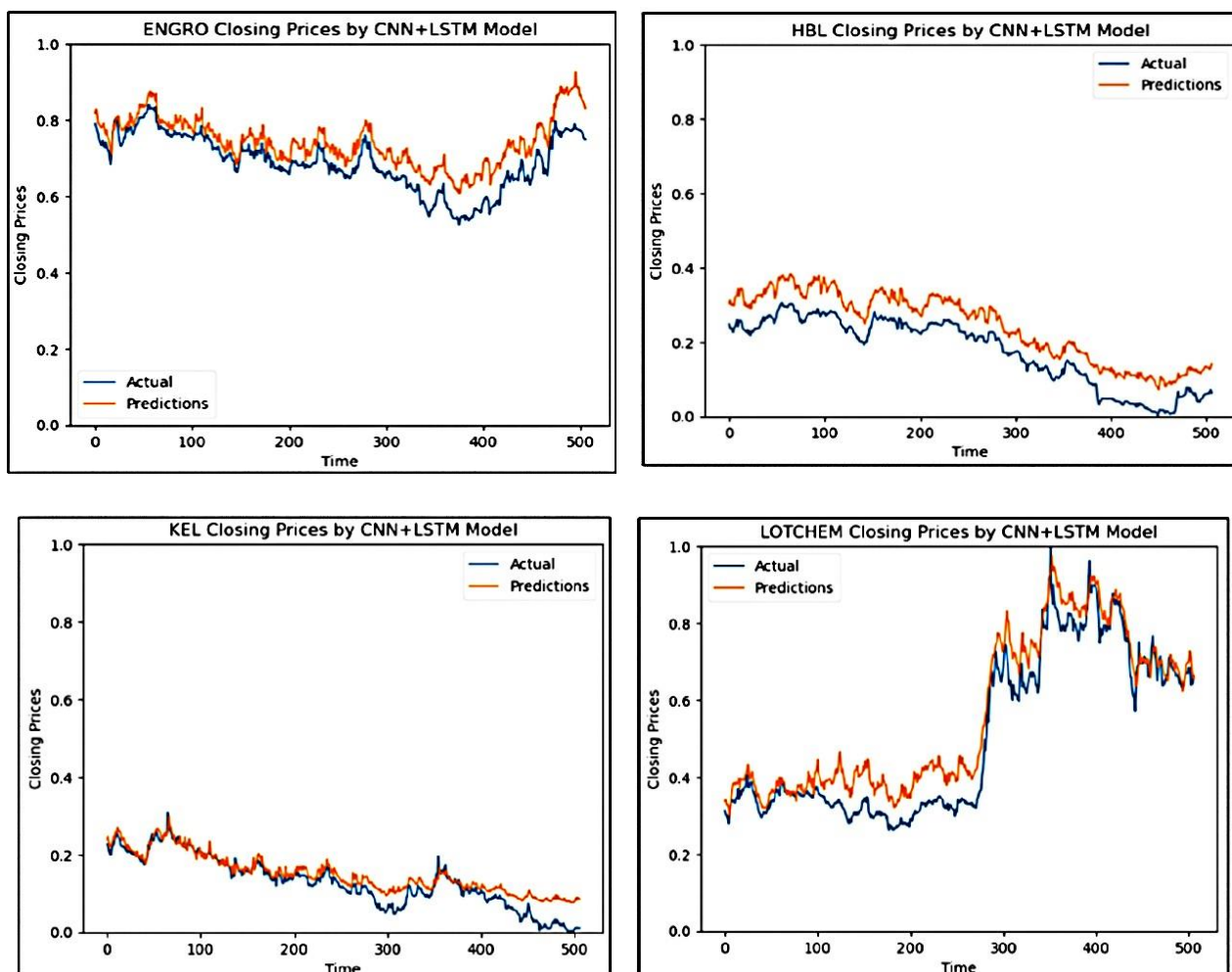
Table 4

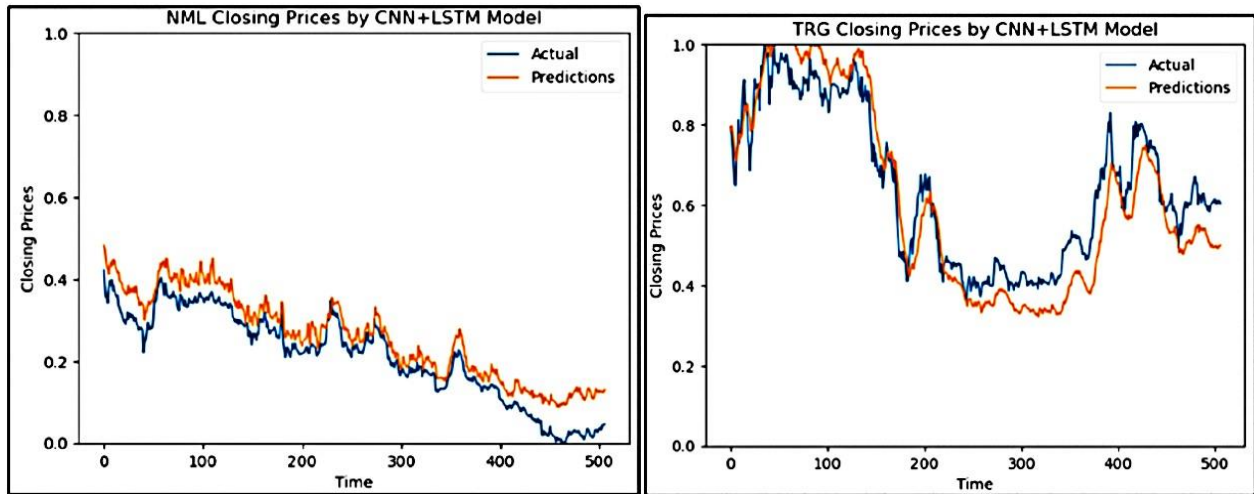
CNN Model Training and Testing Evaluation

Stock	Model Training			Model Testing		
	Avg. MSE	Avg. MAE	Avg. RMSE	Avg. MSE	Avg. MAE	Avg. RMSE
ENGRO	0.00057	0.01774	0.02355	0.00689	0.07614	0.08212
HBL	0.00056	0.01689	0.02348	0.00628	0.07697	0.07855
KEL	0.00048	0.01691	0.02183	0.00064	0.01926	0.02443
LOTCHAM	0.00016	0.00896	0.01266	0.00560	0.06388	0.07278
NML	0.00060	0.01852	0.02435	0.00244	0.04120	0.04847
TRG	0.00035	0.00908	0.01852	0.00859	0.07789	0.09157
	0.00045	0.01468	0.02073	0.00507	0.05922	0.06632

Figure 15

Closing Stock Price Prediction Using CNN+LSTM Model





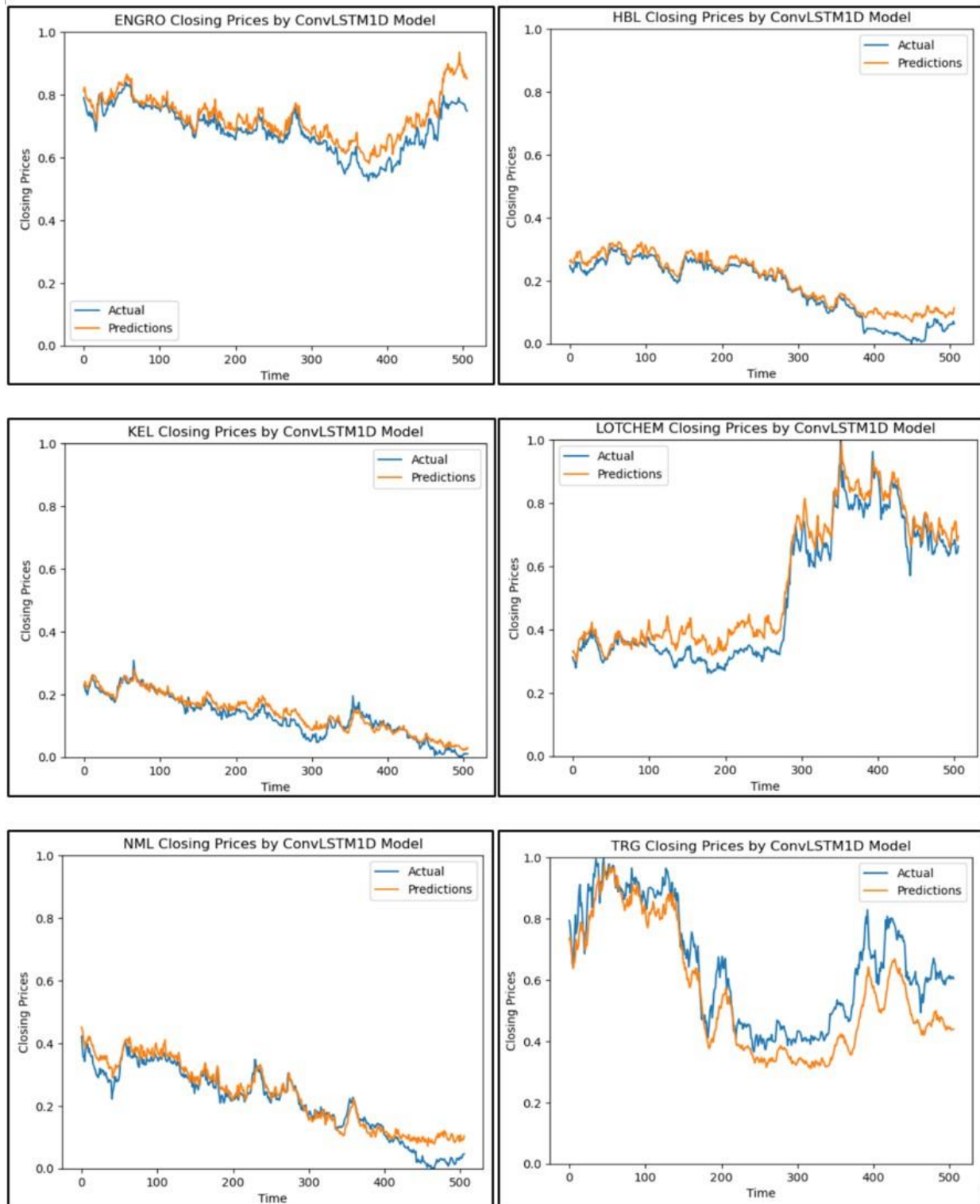
4.6 | Performance of ConvLSTM1D Model for Price Prediction

While the CNN+LSTM model contains separate CNN and LSTM layers, ConvLSTM models combine LSTM and CNN in a single unit. Within the LSTM units, convolution is being performed in ConvLSTM models. This enables simultaneous processing of temporal as well as spatial features, unlike the sequential processing that occurs in CNN+LSTM models. Again, when compared with CNN or LSTM models, the ConvLSTM1D model is more stable across all the stocks with lower error rates. It performs best for KEL and NML stocks.

Table 5

ConvLSTM1D Model Training and Testing Evaluation

Stock	Model Training			Model Testing		
	Avg. MSE	Avg. MAE	Avg. RMSE	Avg. MSE	Avg. MAE	Avg. RMSE
ENGRO	0.00046	0.01622	0.02138	0.00263	0.04093	0.05059
HBL	0.00033	0.01372	0.01799	0.00267	0.04388	0.05105
KEL	0.00055	0.01811	0.02342	0.00098	0.02527	0.03085
LOTCHAM	0.00013	0.00827	0.01153	0.00 482	0.05849	0.06745
NML	0.00057	0.01753	0.02373	0.00138	0.02947	0.03586
TRG	0.00048	0.01001	0.02189	0.01242	0.09623	0.11072
	0.00042	0.01398	0.01999	0.00415	0.04904	0.05775

Figure 16*Closing Stock Price Prediction Using ConvLSTM1D Model***4.7 | Performance of ConvLSTM2D Model for Price Prediction**

While the ConvLSTM1D model is designed for handling one-dimensional data, ConvLSTM2D takes 2-dimensional data as input. The former performs convolution operation on the time dimension and in doing so learns time and spatial dependencies within the time sequence. The later model learns patterns in both time

and space instantaneously. The performance of ConvLSTM2D is comparable to the performance of the ConvLSTM1D model.

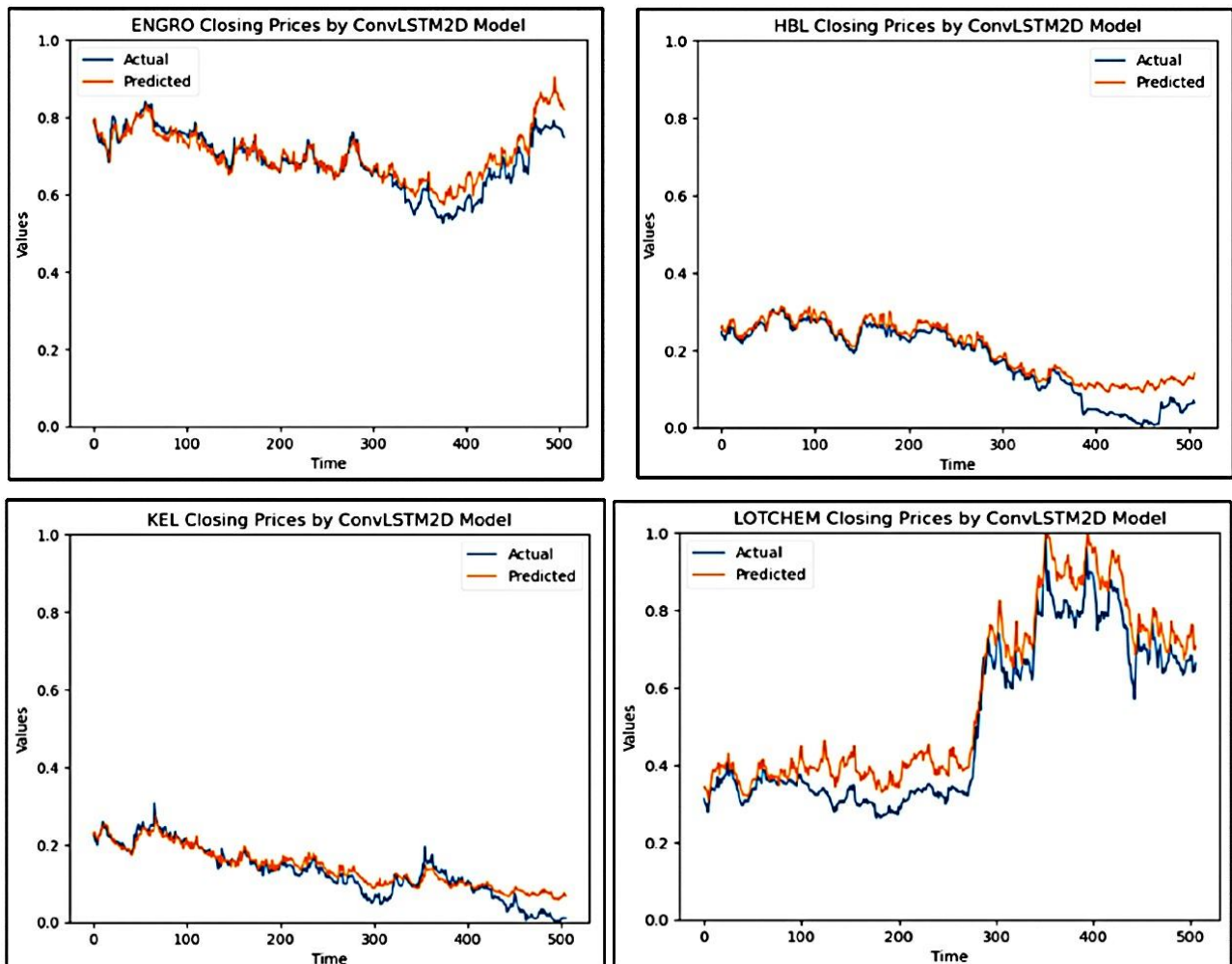
Table 6

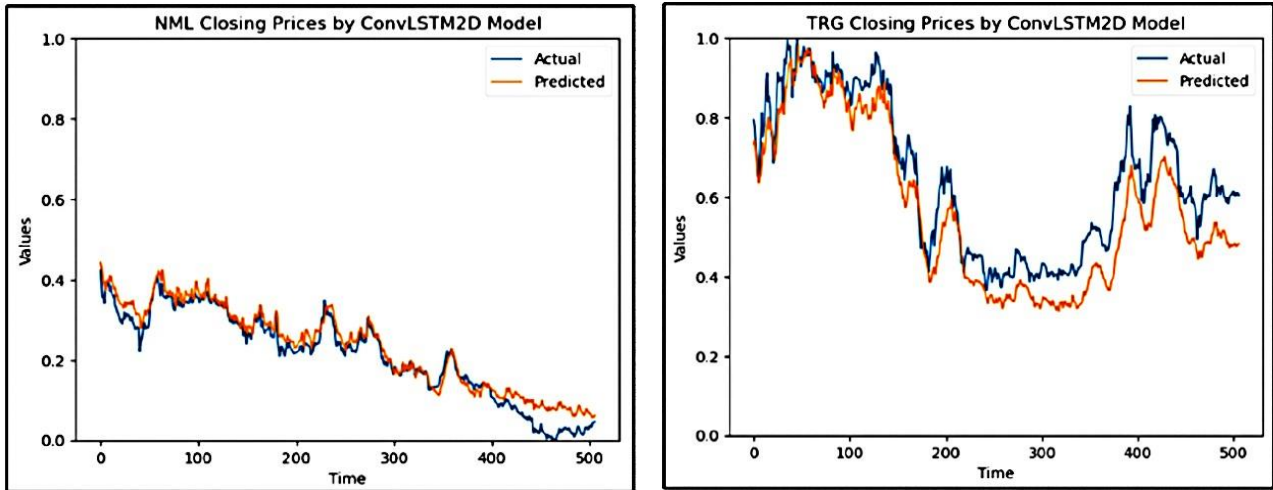
ConvLSTM2D Model Training and Testing Evaluation

Stock	Model Training			Model Testing		
	Avg. MSE	Avg. MAE	Avg. RMSE	Avg. MSE	Avg. MAE	Avg. RMSE
ENGRO	0.00041	0.01507	0.02010	0.00237	0.03832	0.04795
HBL	0.00035	0.01417	0.01845	0.00283	0.04544	0.05190
KEL	0.00049	0.01688	0.02207	0.00086	0.02320	0.02906
LOTCHAM	0.00014	0.00858	0.01182	0.00546	0.06139	0.07053
NML	0.00060	0.01821	0.02433	0.00140	0.03096	0.03678
TRG	0.00049	0.01017	0.02195	0.01240	0.09690	0.11018
	0.00041	0.01385	0.01979	0.00422	0.04937	0.05773

Figure 17

Closing Stock Price Prediction Using ConvLSTM2D Model





5 | FINDINGS

This study hypothesized that the proposed ConvLSTM network architecture provides a consistent best result for next-day closing price predictions in PSX when compared with LSTM, CNN, and CNN+LSTM models since ConvLSTM models can process spatial and time-based patterns together inside a single unit. Model performance results for each selected stock are given in Table 7 – 12. The stated results negate the existence of a universal best model that gives the best results for each stock across MSE, MAE, and RMSE metrics. This indicates that different stocks are affected by different dynamics in the stock market and governed by different forces. Some stocks are strongly dependent upon the past while other stocks are more strongly affected by social, political, and economic events occurring. For companies strongly involved in international trade, changes in the international arena such as sanctions, wars, etc. also have a significant effect on their stock prices. For such stocks that are more affected by events in the surroundings, CNN-based models perform better than LSTM models.

Table 7

Model Training and Testing Evaluation for ENGRO

ENGRO	Training			Testing		
	MSE	MAE	RMSE	MSE	MAE	RMSE
LSTM	0.00041	0.01518	0.02004	0.00078	0.02258	0.02749
CNN	0.00044	0.01557	0.02088	0.00584	0.06911	0.07508
CNN+LSTM	0.00057	0.01774	0.02355	0.00689	0.07614	0.08212
ConvLSTM1D	0.00046	0.01622	0.02138	0.00263	0.04093	0.05059
ConvLSTM2D	0.00041	0.01507	0.02010	0.00237	0.03832	0.04795

Table 8*Model Training and Testing Evaluation for HBL*

HBL	Training			Testing		
	MSE	MAE	RMSE	MSE	MAE	RMSE
LSTM	0.00225	0.02166	0.02743	0.00737	0.05463	0.06085
CNN	0.00041	0.01445	0.02012	0.00422	0.06165	0.06400
CNN+LSTM	0.00056	0.01689	0.02348	0.00628	0.07697	0.07855
ConvLSTM1D	0.00033	0.01372	0.01799	0.00267	0.04388	0.05105
ConvLSTM2D	0.00035	0.01417	0.01845	0.00283	0.04544	0.05190

Table 9*Model Training and Testing Evaluation for KEL*

KEL	Training			Testing		
	MSE	MAE	RMSE	MSE	MAE	RMSE
LSTM	0.00051	0.01718	0.02249	0.00181	0.03287	0.04017
CNN	0.00053	0.01737	0.02289	0.00116	0.02691	0.03190
CNN+LSTM	0.00048	0.01691	0.02183	0.00064	0.01926	0.02443
ConvLSTM1D	0.00055	0.01811	0.02342	0.00098	0.02527	0.03085
ConvLSTM2D	0.00049	0.01688	0.02207	0.00086	0.02320	0.02906

Table 10*Model Training and Testing Evaluation for LOTCHEM*

LOTCHEM	Training			Testing		
	MSE	MAE	RMSE	MSE	MAE	RMSE
LSTM	0.00375	0.03140	0.03937	0.04823	0.12332	0.14758
CNN	0.00018	0.00933	0.01323	0.00375	0.05147	0.06069
CNN+LSTM	0.00016	0.00896	0.01266	0.00560	0.06388	0.07278
ConvLSTM1D	0.00013	0.00827	0.01153	0.00482	0.05849	0.06745
ConvLSTM2D	0.00014	0.00858	0.01182	0.00546	0.06139	0.07053

Table 11*Model Training and Testing Evaluation for NML*

NML	Training			Testin g		
	MSE	MAE	RMSE	MSE	MAE	RMSE
LSTM	0.00054	0.01682	0.02326	0.00158	0.03126	0.03918
CNN	0.00060	0.01837	0.02419	0.00219	0.03920	0.04492
CNN+LSTM	0.00060	0.01852	0.02435	0.00244	0.04120	0.04847
ConvLSTM1D	0.00057	0.01753	0.02373	0.00138	0.02947	0.03586
ConvLSTM2D	0.00060	0.01821	0.02433	0.00140	0.03096	0.03678

Table 12*Model Training and Testing Evaluation for TRG*

	Training			Testing		
	MSE	MAE	RMSE	MSE	MAE	RMSE
LSTM	0.00120	0.01275	0.02826	0.03479	0.14571	0.16200
CNN	0.00079	0.01146	0.02774	0.02774	0.15164	0.16333
CNN+LSTM	0.00035	0.00908	0.01852	0.00859	0.07789	0.09157
ConvLSTM1D	0.00048	0.01001	0.02189	0.01242	0.09623	0.11072
ConvLSTM2D	0.00049	0.01017	0.02195	0.01240	0.09690	0.11018

Most accurate predictions for ENGRO are given by the LSTM model indicating that ENGRO stock exhibits strong time sequences and patterns which were captured by the LSTM model. In the case of LOTCHEM stock, the CNN model provides the best results in comparison to other models that are part of the study. This highlights the presence of significant spatial dependencies of closing prices on the input features such as technical indicators, market sentiment, economic indicators, and related stocks that CNN was able to learn effectively. For TRG and KEL, the CNN+LSTM model gives the best results while ConvLSTM models provide the most accurate predictions for NML and HBL showing that these stocks are influenced by both events occurring in their surroundings as well as their previous price patterns and trends.

While ConvLSTM models may not provide the most accurate predictions for each stock, the said models are much more consistent when compared with other models. If the performance of each model during training and testing across all stocks is averaged, ConvLSTM models exhibit the best performance across all three evaluation measures. Among the two ConvLSTM models, ConvLSTM1D provides the best average results across each stock. Results in summarized in Table 13.

Table 13*Average Training and Testing Evaluation Results for all Stocks*

Average Performance	Training			Testing		
	MSE	MAE	RMSE	MSE	MAE	RMSE
LSTM	0.00144	0.01917	0.02681	0.01576	0.06839	0.07954
CNN	0.00049	0.01443	0.02151	0.00748	0.06666	0.07332
CNN+LSTM	0.00045	0.01468	0.02073	0.00507	0.05922	0.06632
ConvLSTM1D	0.00042	0.01398	0.01999	0.00415	0.04904	0.05775
ConvLSTM2D	0.00041	0.01385	0.01979	0.00422	0.04937	0.05773

If a single model is to be chosen for predicting the next day closing price prediction of all of the selected stocks, predictions provided by the ConvLSTM1D model have the lowest average MSE, MAE, and RMSE values. It is to be noted that the ConvLSTM1D model is not a universal model. Rather, when using the said model for making price predictions for different stocks, the model performance will vary across each stock.

However, on average ConvLSTM1D provides the best results even though the optimal model for an individual stock may be different.

5 | DISCUSSION

The fact that different models perform best for different stocks points towards the fact that stock behaviour varies across the market. LSTM models are better equipped at capturing temporal sequences than any of the other models discussed in this research. Hence, the said algorithm works best with stocks that exhibit strong temporal dependencies. For some stocks, price is strongly dependent upon events in the surroundings in the near past. The presence of such spatial dependencies makes CNN-based algorithms an ideal choice. For stocks that exhibit both long-term time dependencies as well as short-term dependency on happenings in the surroundings, a combination of CNN and LSTM outperforms either of the constituent algorithms. Both CNN + LSTM and ConvLSTM can capture temporal as well as spatial dependencies, however, how these interactions are captured differs in both models. CNN + LSTM network contains separate layers of CNN and LSTM layers whereas in ConvLSTM, both LSTM incorporate convolution operation within the LSTM cell. Where spatial and temporal features are captured sequentially in CNN + LSTM layers, these features are captured simultaneously in ConvLSTM. Since CNN + LSTM networks have separate CNN and LSTM layers, such a network is more suitable for stocks with prices strongly dependent upon multiple factors in the environment as well as historical prices that are not closely connected. But when a complex and intermingled relationship exists between events in surroundings and historical prices i.e. historical prices of stock influence the environment and the changes in the environment in turn affect the stock prices, the performance of ConvLSTM models exceeds all other variants.

Hence, the prediction results provide insight into the behaviour of different stocks. ENGRO stock is strongly dependent upon its historical prices so investors looking to invest in ENGRO stock should focus more on past trends and movements. Similarly, short spatial dependencies are significant for LOTCHEM stock and should be the primary focus of concern. For KEL, NML, TRG, and HBL, both spatial dependencies as well as long-term temporal dependencies significantly influence future prices. However, the interaction between spatial and temporal features for HBL and NML is much more complex than the same in KEL and TRG; hence, ConvLSTM performs best for these two stocks.

6 | CONCLUSION

The existing literature developed ConvLSTM architecture predicting next-day closing stock prices for the Chinese stock market (Tao et al., 2022). After comparison with other deep learning models, their results showed that the ConvLSTM model was universal for Chinese stocks and consistently provided the best performance across all the selected evaluation measures in the study. However, it is pertinent to point out the differences between the quoted study and the findings of this research. In the quoted study (Tao et al., 2022), the network architecture for the ConvLSTM model and other deep learning models involved in the study was not the same. Other deep learning models were implemented using their basic structure. Moreover, the specific study involved the production of feature vectors for each input feature. Final predictions were achieved after concatenating the feature vectors and passing these concatenated vectors through a dense. In this study, the main network architecture for all deep learning models is the same barring some minor changes that were

necessitated by the model's dimensional requirements. Moreover, input feature processing is the same across all the models. Therefore, the results of this study do not stand in opposition to the quoted research.

The research used the ConvLSTM1D model for next-day closing price prediction for TCS and MRF stocks in the Indian stock market (Jain et al., 2018). The authors concluded that the ConvLSTM1D model performs better when compared with CNN and LSTM models; however, hyper-parameters for the model need to be adjusted as per the stock under consideration. Thus, this study rules out the existence of a universal model amongst CNN, LSTM, and ConvLSTM1D for stock price prediction if hyperparameters are not adjusted for each stock. Hence, the results of this research corroborate the mentioned study. With the same model architecture and hyper-parameter settings, no universal model was found that consistently gave the best performance across MSE, MAE, and RMSE evaluation measures for the six stocks selected from PSX (KSE-100).

6.1 | Future Research Directions

Research could be undertaken to find the optimal hyperparameters for the ConvLSTM model such as the number of nodes in the layer, choice of optimizer, choice of activation function, learning rate, epoch size, batch size, mutation point handling factors, and different sentiment analysis techniques. Moreover, this study can be used as a base to create a stock recommendation engine / algorithmic trading application since the model includes many essential inputs for such applications such as technical indicators, market sentiment, and macroeconomic environment indicators. Furthermore, this research can be extended to the field of portfolio optimization and risk assessment.

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