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Stock market liquidity: hybrid deep learning approaches for prediction

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ABSTRACT

Predicting stock market liquidity especially in emerging or frontier financial markets, such as the Casablanca stock exchange (CSE), presents significant challenges given the relative narrowness and volatility of these markets. In this paper, we conduct a comprehensive study to address the predictions accuracy gaps between five main deep learning models: convolutional neural network (CNN), long short-term memory (LSTM), bidirectional LSTM (BiLSTM), and two hybrid architectures, CNN-LSTM and CNN-BiLSTM. The proposed methodology focused on training and testing these models on historical data from the CSE, with precision on capturing both spatial and temporal market dynamics. The models were fine-tuned using key hyperparameters and validated on 20% of the dataset to ensure reliable results. The evaluation of performance was conducted using error metrics such as mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE). The study demonstrates that the hybrid CNN-biLSTM model consistently outperformed all standalone and other hybrid models in predictive accuracy. This underscores the considerable promise of hybrid deep learning architectures for addressing the unique challenges of predicting stock market liquidity in volatile and emerging financial markets.

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1. INTRODUCTION

Stock market liquidity prediction in volatile environments, such as the Casablanca stock exchange (CSE), holds significant importance for various market participants, including investors, issuers, and regulators. However, conventional prediction techniques frequently struggle to adequately capture the complex and nonlinear dynamics of financial data, particularly in emerging or frontier markets characterized by limited transparency. Market microstructure anomalies, such as discrepancies in bid-ask spreads or trading volumes, introduce additional complexities in predicting liquidity, along with volatility and distinct structural influences [1]. Consequently, researchers have increasingly explored machine learning models, particularly deep learning architectures, due to their proficiency in handling extensive datasets and complex patterns [2]–[4]. In this context, hybrid models that combine convolutional neural networks (CNN) and long short-term memory networks (LSTM) expressed remarkable predictive performance. Nonetheless, their application in developing financial contexts, such as Morocco, remains underexplored [5], [6].

Deep learning models have gained significant attention for stock market prediction because of their capacity to recognize intricate patterns within time series data. Models such as CNNs have been highly effective at extracting features, whereas LSTMs demonstrate strong capabilities in capturing temporal dependencies, particularly in dynamic environments [7]. Hybrid models, such as the CNN-LSTM and CNN-bidirectional LSTM (BiLSTM), have shown promising results by uniting the strengths of spatial and temporal pattern recognition. While LSTMs are commonly used for stock price forecasting due to their ability to capture temporal sequences, they often struggle with generalization when applied to unfamiliar financial environments. BiLSTM models enhance LSTMs by effectively capturing dependencies from both the past and future. However, they come with increased computational costs and extended training durations [7]. Hybrid CNN-LSTM models offer a promising solution to improve prediction accuracy by capturing both local patterns and long-term dependencies. Nonetheless, these models are highly sensitive to hyperparameters, making them challenging to optimize for real-world applications [8]–[13]. The hybrid CNN-BiLSTM architecture, which combines CNN's spatial feature extraction with BiLSTMs temporal modeling, has shown even greater promise, but its application in dynamically shifting and growth-oriented markets remains largely unexplored [14]–[22].

The objective of this study is to evaluate and compare the predictive accuracy of various deep learning architectures for forecasting stock market liquidity in emerging financial markets, using the CSE as a case study. Specifically, we investigate five models: CNN, LSTM, BiLSTM, and two hybrid models, CNN-LSTM and CNN-BiLSTM. Using the financial times stock exchange (FTSE) CSE Morocco 15 index as a key indicator of the CSE, we evaluate these models through error metrics such as mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) to determine their efficacy in forecasting market liquidity. The choice of these models is based on their ability to accurately represent the temporal dependencies and spatial patterns present in financial time series data. The goal is to determine which model best captures the complex temporal and spatial patterns in stock market data, providing a reliable forecasting tool for market participants in volatile environments.

The findings aim to fill a significant gap in the literature regarding deep learning applications in the context of developing countries. This study strives to systematically assess various model designs to provide essential guidance for financial professionals, market regulators, and investors, aiding their decision-making in unpredictable scenarios. The paper is structured as follows: section 2 describes the data sources, model architectures, training and validation setup, and evaluation metrics used to measure model performance. Section 3 presents a detailed comparison of the models, interpreting the performance metrics and comparing them against existing literature to highlight the strengths and limitations of each model, while section 4 summarizes the key results, examines practical consequences, and proposes avenues for further study to improve stock market liquidity prediction in developing markets.

2. METHODOLOGY

This section delineates a comprehensive guideline for the methodological phases of the study, starting from database collection and pre-processing, followed by model's architectures, training, testing and hyperparameters fine-tuning.

2.1. Dataset description

The dataset utilized in this study is publicly accessible on the official website of the CSE, covering the most recent 5 years period [23]. Table 1 presents a sample of the features extracted from the dataset. The feature names have been translated from French into English for clarity. Before moving to the next step in the dataset processing, it is important to highlight that in addition to the described features we calculated a key feature named the "Bid-Ask-Spread", which represents a key measure used to gauge trading frictions, where a larger spread indicates lower liquidity and higher implicit costs for traders by leveraging complete open, high, low, and close price data which ensure more accurate spread estimates, essential for empirical finance and practical applications in asset pricing and regulatory analysis, providing a comprehensive view of the situation [24], [25]. Table 2 snapshot the dataset format.

Afterwards, and to ensure the models reliability, we devoted 80% of data for training and 20% was evenly divided between testing and validation. The training sequences supports comprehensive learning, while the validation set enables fine-tuning. The separate testing set, provides an objective measure of generalization to unseen data.

2.2. Models selection

In this study, we examine multiple deep learning architectures to effectively capture both local and long-term dependencies present in the stock market data. The selection of each model architecture was driven by its ability to handle different facets of financial data. The parameterization of each model was also carefully considered.

Table 1. Dataset default features

Feature	Translation	Description
Séance	Session date	The date of the session
Valeur indice	Index value	Session stock index value
Plus haut	Highest value	Highest session index value
Plus bas	Lowest value	Lowest session index value
Variation veille	Previous day change	The percentage change in the index value compared to the previous day
Variation 31/12	Year to date change	The year-to-date percentage change in the index value, presumably measured from December 31st of the previous year

Table 2. Overview of the CSE dataset features format

Séance	Valeur indice	Plus haut	Plus bas	Variation veille	Variation 31/12	Bid-Ask Spread
2021-01-04	10317.51	1031.75	10225.50	0.90	0.90	92.25
2021-01-05	10261.66	10323.29	10261.66	-0.54	0.35	61.63
2021-01-06	10233.11	10304.18	10219.33	-0.28	0.07	84.85
2021-01-07	10288.08	10329.4	10233.11	0.54	0.61	96.83
2021-01-08	10269.53	10311.30	10266.89	-0.18	0.43	44.41

2.2.1. Convolutional neural networks

Figure 1 illustrates the architecture of CNN, a class of deep learning, specifically neural networks, designed for image processing and computer vision tasks designed for image processing and computer vision tasks. These networks are particularly adept at recognizing spatial patterns within grid-like data, which was adapted to handle time-series nature for stock market predictions by capturing short-term patterns in financial data sequences [26], [27]. The architecture of the CNN is composed of three main layers: convolutional, pooling, and fully connected layers. Convolutional layers constitute the fundamental framework of CNNs. Filters, also known as kernels, are applied as they traverse the input data, resulting in the creation of feature maps, which emphasize significant local patterns in the data, such as swift changes in stock prices, by concentrating on spatially adjacent data points. In this model, the filter size was chosen through empirical trials, striking a balance between capturing relevant patterns and maintaining computational efficiency, which is essential to preserve important features on the dataset. Finally, the fully connected layers consolidate input from the convolutional and pooling layers to produce a single neuron that forecasts stock market liquidity.

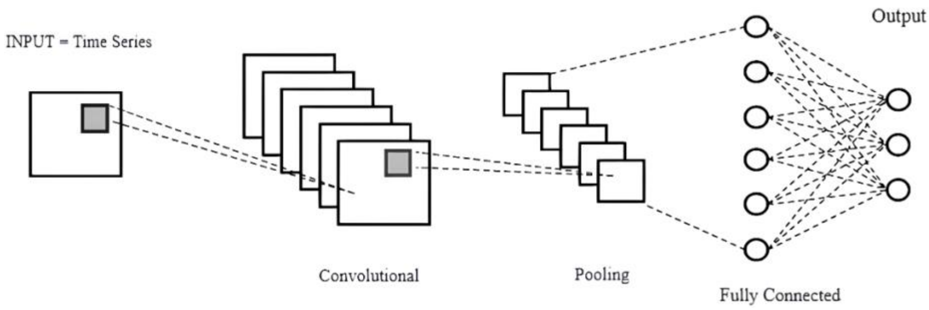

Figure 1. The CNN architecture

The CNN designed in this study, initiates with a Conv1D layer that includes 64 filters and a kernel size of 3, applying the rectified linear unit (ReLU) activation function. This convolutional layer detects local patterns in the input data through the application of filters across the time steps, also capturing significant short-term trends. Next, a MaxPooling1D layer is implemented with a pool size of 2, which effectively reduces the dimensionality of the feature maps through down-sampling, thus preserving essential features while minimizing computational complexity. The output from the pooling layer is subsequently flattened, transforming the 1D feature maps into a singular vector suitable for input into fully connected layers. Subsequently, a dense layer comprising 50 neurons with ReLU activation facilitates the model's ability to comprehend intricate interactions among features. The concluding layer is a dense output layer featuring a single neuron, which delivers the model's prediction for regression tasks. The model utilizes the Adam optimizer to facilitate effective learning via adaptive gradient estimation, while MSE is selected as the loss function to emphasize precise predictions by imposing penalties on larger errors.

Furthermore, the MAE is incorporated as a performance metric to enhance interpretability regarding the average deviation from actual values.

2.2.2. Long short-term memory

Unlike to recurrent neural network (RNN), which experience challenges with the vanishing gradient problem, LSTM networks are specifically designed as a variant of RNNs to effectively capture long-term dependencies in sequential data. Figure 2 portrays the architecture of this category of neural networks that leverage memory cells to preserve crucial information across prolonged sequences, rendering them appropriate for time-series data. The LSTM cell consistently involves three fundamental gates: input, forget, and output. The input gate determines the information to store, the forget gate identifies which information to eliminate, and the output gate regulates the final output according to the current cell state and prior outputs [28]–[30]. The architecture of the study sets up with an LSTM layer comprising 100 units, utilizing the default return sequences parameter. This configuration permits the model to produce the complete sequence of hidden states, which simplifies the subsequent LSTM layer's access to sequential information, which is important for acquiring intricate temporal dependencies across various time steps, and to further evaluate this information and generate a final hidden state that encapsulates the learned temporal features up to the current time step, an additional LSTM layer is constructed. This layer consists of one hundred units and does not engage the return sequences parameter. Subsequently, the output from the LSTM layers is sent to a Dense layer consisting of a solitary neuron. This layer generates the ultimate prediction for regression problems. This model was constructed with the Adam optimizer, selected for its customizable learning rate attributes. These characteristics result in training methodologies that are both effective and reliable. Furthermore, the MSE serves as the loss function to inflict a greater penalty on substantial prediction errors, hence enhancing the accuracy of stock market predictions. The MAE is a performance metric that elucidates average deviations, hence improving comprehension of the model's predictive efficacy.

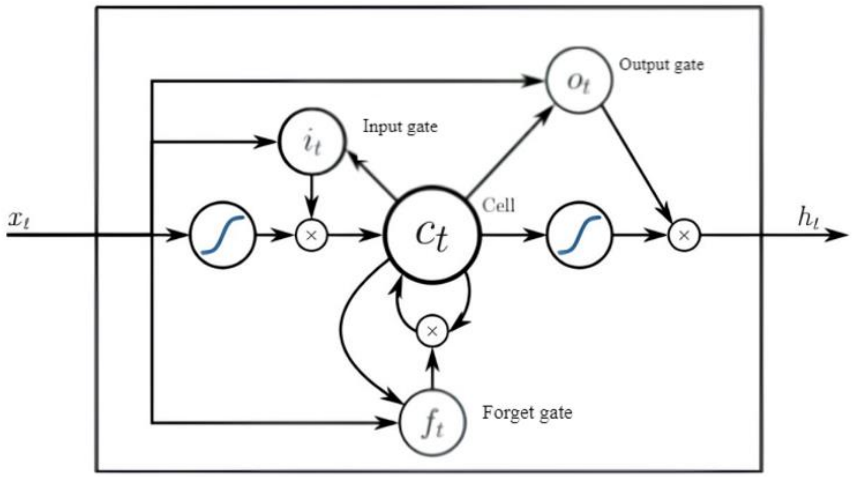

Figure 2. The LSTM network architecture

2.2.3. Bidirectional long short-term memory

BiLSTM networks are an advanced form of LSTM designed to identify patterns in sequential data by processing it in forward as well as backward directions. This bidirectional processing permits LSTMs to acquire more extensive temporal patterns, rendering them especially useful in situations where both past and future contexts improve prediction accuracy for stock market forecasting as illustrated in Figure 3. They are particularly effective, because they capture dependencies that might not be apparent when only past information is considered [30]–[32]. To create this model, we retained the LSTM setup outlined in the preceding section and just triggered the bidirectional process.

2.2.4. CNN-LSTM and CNN-BiLSTM

The hybrid CNN-LSTM or CNN-BiLSTM models combines the advantages of CNN and LSTM/BiLSTM while adhering to the configuration described in the previous section. Both approaches use CNN for spatial feature extraction and LSTM for temporal learning. However, the CNN-biLSTM model offers a second viewpoint on sequence data, possibly enhancing accuracy in settings where comprehension of both past and future is beneficial.

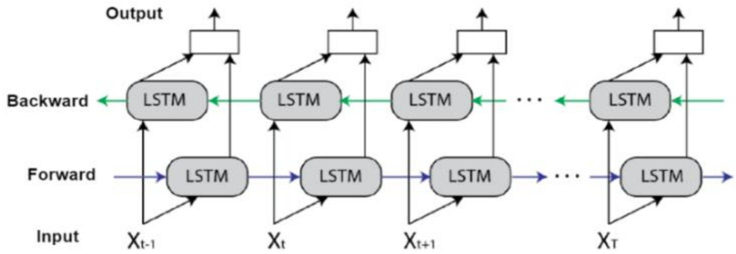

Figure 3. The BiLSTM architecture

2.3. Hyperparameter tuning and optimization

Over the training process, we optimized hyperparameters in accordance with deep learning principles, performing repeated experiments to enhance performance by identifying the ideal configurations for batch size, dropout rates, and learning rates, therefore balancing computing efficiency with model efficacy. The batch size was set to 30, balancing computational efficiency with the model's ability to generalize. We fixed the number of epochs at 100, providing enough iterations for the model to thoroughly learn the underlying data patterns without overfitting. The hyperparameters were fine-tuned through multiple iterations, testing various configurations to ensure optimal performance across both training and validation datasets. This process involved continuous monitoring of not just the final prediction accuracy but also the model's capacity to generalize well to unobserved data, thus reducing the risk of overfitting. The manual iteration technique facilitated modest modifications to hyperparameters, allowing a concentrated analysis of the impact of each configuration on model correctness and stability. This technique has inherent drawbacks, especially the time-consuming process of manually adjusting several parameters. Moreover, manual tuning may fail to identify the definitive ideal settings due to human limitations in methodically examining the whole hyperparameter space. For evaluating model performance during training, MSE was selected as the loss function. MSE penalizes larger errors more heavily, making it an ideal metric for regression problems like stock market prediction, where precise forecasting is crucial. By focusing on minimizing significant deviations between predicted and actual values, MSE helps improve the model's accuracy and reliability in real-world applications. The selection of MSE also ensured that the model would prioritize reducing larger errors, enhancing its robustness in predicting stock market liquidity accurately.

3. RESULTS AND DISCUSSION

This section presents a comparative performance analysis of the proposed deep learning architectures, including CNN, LSTM, BiLSTM, and hybrid CNN-LSTM and CNN-BiLSTM models, in forecasting stock market liquidity within the volatile context of the CSE. Our findings validate prior research, demonstrating that CNN-BiLSTM models excel in environments requiring the identification of both spatial and temporal patterns, such as fluctuating financial markets. The existing literature highlights a notable limitation in the utilization of deep learning for predicting volatile stock markets. This study addresses this gap by demonstrating that the CNN-BiLSTM model can effectively manage the distinct challenges presented by developing markets such as Morocco's, which include rapid fluctuations and unusual market behaviors. Table 3 summarizes the performance of models in terms of key error metrics (MSE, RMSE, and MAE) and Figures 4 to 8 demonstrates the learning curves which proves the superior performance of CNN-BiLSTM and indicates a viable avenue for financial analysts and investors looking for dependable liquidity forecasts in developing or emerging markets.

Table 3. Performance comparison of trained models

Model	MSE	RMSE	MAE
CNN	0.014874	0.121957	0.092361
LSTM	0.005839	0.076415	0.050488
BiLSTM	0.005972	0.077280	0.048909
CNN-LSTM	0.004838	0.069556	0.044244
CNN-BiLSTM	0.004742	0.068859	0.048855

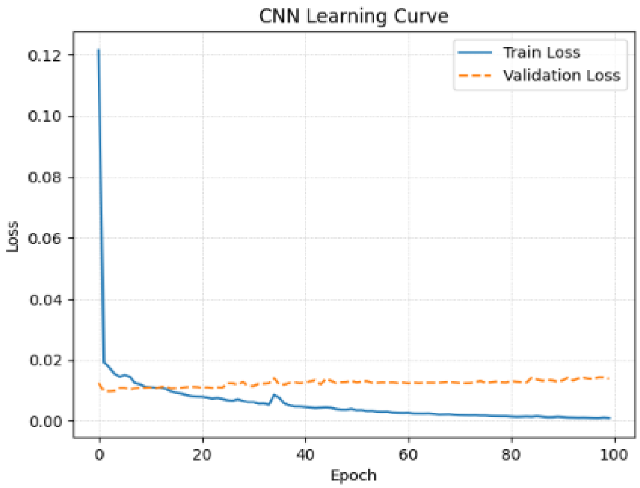

Figure 4. The CNN learning curve

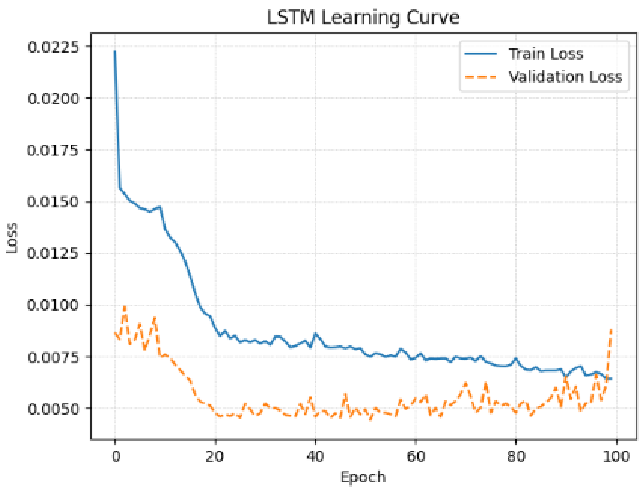

Figure 5. The LSTM learning curve

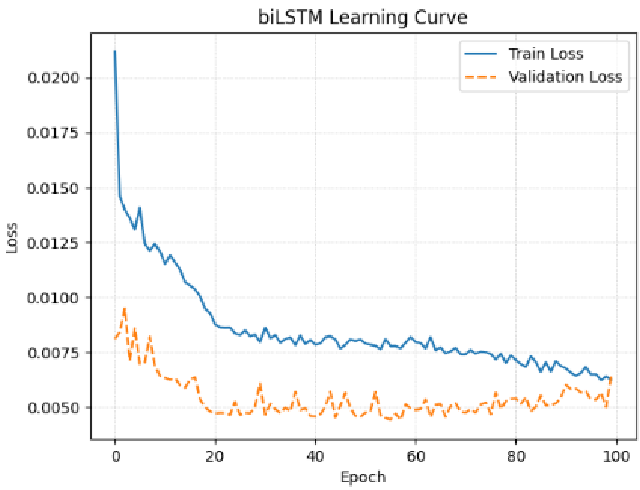

Figure 6. The BiLSTM learning curve

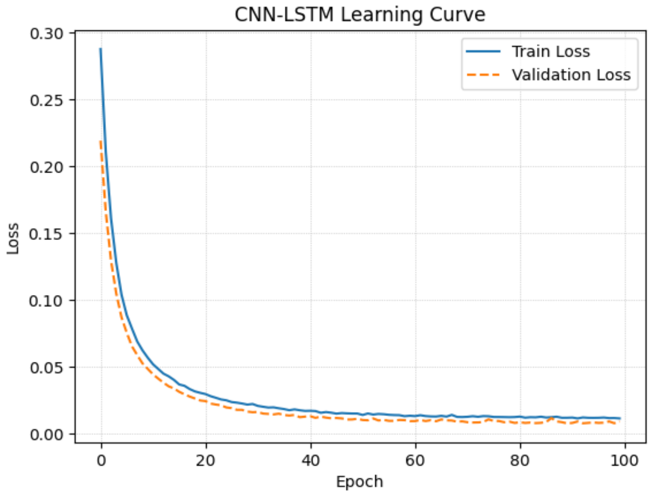

Figure 7. The CNN-LSTM learning curve

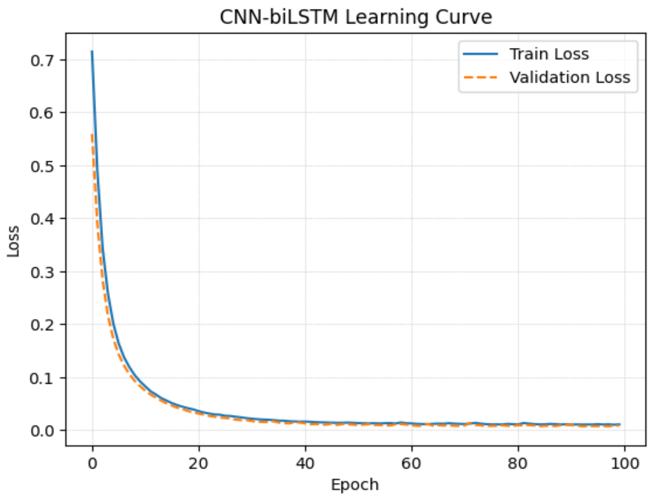

Figure 8. The CNN-BiLSTM learning curve

The demonstrated accuracy of hybrid models, specifically CNN-BiLSTM, suggests a promising direction within developing markets. The hybrid deep learning models can inform investment strategies and regulatory decisions, eventually improving market stability and investor confidence on the market movements. Additionally, deploying this solution in a real-world environment will facilitate better decision-making, especially under unstable economic conditions. While this study offers valuable insights, several limitations should be noted. First, the analysis focuses only on one stock exchange CSE, which may limit how well the results apply to other developing markets with different economic conditions. Additionally, the model's hyperparameters were set manually, which might not be optimal; future work could improve this by using automated tuning methods. Including external economic factors, could also make the model more robust and better reflect the broader economic environment affecting market liquidity. Figure 9 represents the use of the CNN-BiLSTM model to forecast stock market liquidity for months excluded from the initial dataset, which proves the model's predictive precision and dependability in practical contexts. The discrepancies between the actual and projected values over this lengthy duration are often minimal, suggesting that the model effectively extends its applicability to novel data without much deviation. This application provides a valuable comparison point with the original dataset's residuals, showing a similarly narrow spread around zero which reinforces the robustness of the CNN-BiLSTM model, demonstrating its potential for accurate forecasting in volatile and dynamic markets.

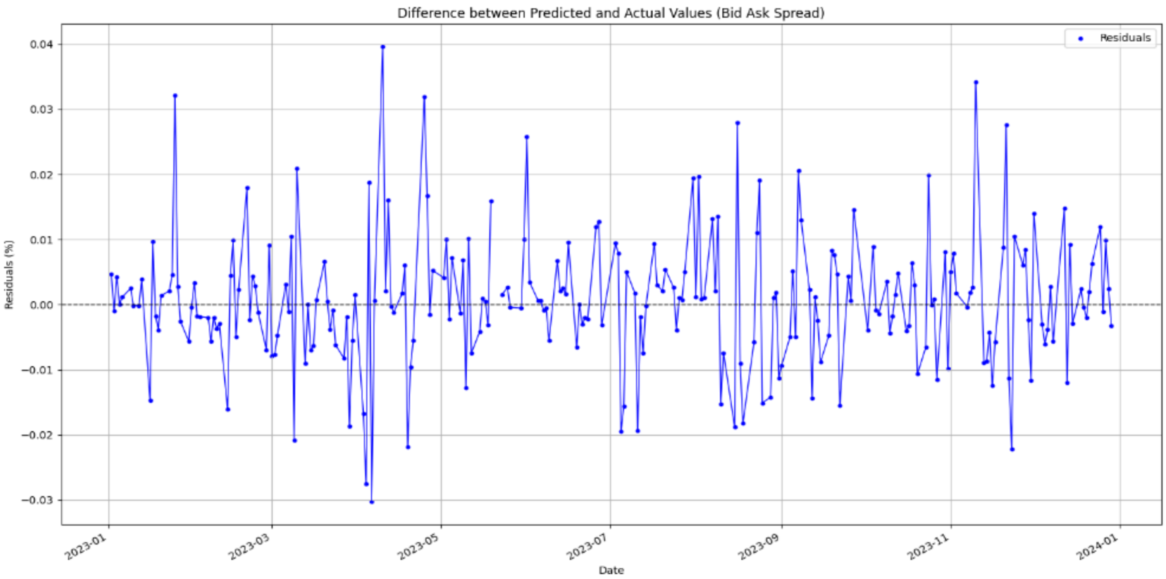

Figure 9. Residual plot of CNN-biLSTM predictions

4. CONCLUSION

Given the academic and professional importance of the stock market liquidity, especially within emerging countries, we try in this study to evaluate and compare different neural networks architectures to predict the future level of this strategic financial variable. As a result, we argue that the hybrid deep learning models are more suitable, especially the combination of CNN and Bi-LSTM within a hybrid framework. We apply this promising approach to one of most active stock markets in Middle East and North Africa (MENA) region i.e., the CSE and provide evidence of its performance for effectively tackling this pressing issue. Despite the significant nature of the results, this study should be completed and enriched. In this context, the proposed approach can serve as a basis for ongoing theoretical improvement and empirical broader investigation. Moreover, and given the strategic importance of market liquidity prediction for investors, it would be important to further extend and deepen the study to provide a practical tool that can be applied in stock market decision-making processes.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Said Achchab	✓	✓	✓	✓	✓	✓	✓			✓	✓	✓	✓	
Younes Lahrichi	✓	✓		✓	✓	✓	✓			✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available at https://www.casablanca-bourse.com, reference number [23].

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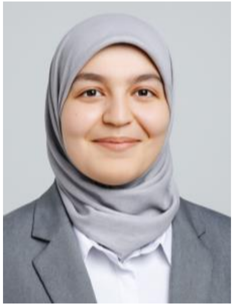

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