CLAM: A Synergistic Deep Learning Model for Multi-Step Stock Trend Forecasting

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Abstract

This paper introduces CLAM, a hybrid deep learning framework that integrates CNNs, LSTMs, and Attention Mechanism (AM) for straightforward multi-step stock trend forecasting. By leveraging CNNs for spatial feature extraction, LSTMs for capturing temporal dependencies, and AM for dynamically focusing on relevant data, CLAM significantly outperforms traditional models in predictive accuracy. Evaluated on diverse stock datasets from different industries, CLAM demonstrates an average reduction of over 80% in MAE and RMSE compared to standalone CNN, LSTM, and fused CNN-LSTM. The model's ability to capture both short-term and long-term trends is particularly advantageous for real-time financial trading, resulting in 75% trend prediction accuracy, with most cases witnessing consecutive accurate forecasts of flash crashes or uptrends, which aids in strategic investment decisions and risk management. Code and data are available at: https://anonymous.4open.science/r/CNN-LSTM-AM-AB13/src/CLAM.ipynb.

Keywords

Deep Learning, Hybrid Model, Stock Markets, Attention Mechanism, Trend Prediction

Introduction

Concerning the evolving industrial landscape, technological innovation and financial strategy intersection has become vital Porter (1985). Artificial Intelligence (AI) is leading this transformation, with advanced neural network architectures such as Convolutional Neural Networks (CNNs) LeCun et al. (1998), Recurrent Neural Networks (RNNs) Mikolov et al. (2010), Long Short-Term Memory Networks (LSTMs) Hochreiter and Schmidhuber (1997a), and Transformers Vaswani et al. (2017) driving advancements in healthcare Esteva et al. (2019) and meteorology Ham et al. (2019) is well-recognized. Nevertheless, its influence on finance is the most promising Nguyen et al. (2015) as the digital economy amplified the role of Machine Learning (ML) in financial markets, where predictive modeling is essential for forecasting stock prices Gu et al. (2018) and informing investment strategies Henrique and Sobreiro (2019). Recovering from the pandemic, the need for precise financial predictions has grown strongly Sharif et al. (2021). Investors increasingly rely on algorithmic modeling to navigate through market complexities, thereby capitalizing on opportunities from quantitative trading of stocks Hagenau et al. (2013).

Traditional models such as ARIMA (Autoregressive Integrated Moving Average) Box et al. (2015), SARIMA (Seasonal ARIMA) De Gooijer and Hyndman (2011), and Linear Regression Montgomery et al. (2012) are predicated on the assumption that historical patterns and trends can effectively predict future stock prices. However, the non-linear nature of stock movements often introduces significant biases in these models Tsay (2005), which tend to oversimplify complex financial dynamics by assuming fixed data variance and linearity Cont (2001). This simplification overlooks critical factors influencing stock prices over time, such as macroeconomic indicators Fama (1981), market sentiment Baker and Wurgler (2006), and herd behavior Bikhchandani et al. (1992). The emergence of Machine Learning (ML) and Deep Learning (DL) models has addressed many of these limitations Hochreiter and Schmidhuber (1997a). Techniques like Support Vector Machines (SVM) Vapnik (1995), Decision Trees Breiman et al. (1984), and Random Forest Regression (RFR) Liaw and Wiener (2002) have advanced the ability to capture non-linear relationships by integrating multiple features and learning from large, complex datasets Chong et al. (2017). DL, as a subset of ML, has further transformed forecasting with deep neural architectures like CNNs LeCun et al. (1998), RNNs Mikolov et al. (2010), and LSTMs Hochreiter and Schmidhuber (1997a), employing hierarchical end-to-end learning that excels in handling unstructured data and scaling with increasingly large time series datasets Zhu et al. (2018). Additionally, hybrid models that combine elements of traditional statistical methods with ML and DL techniques are reshaping the forecasting landscape Zhang et al. (2017). These hybrid approaches, by integrating multiple modalities, enhance feature extraction and provide deeper insights into data irregularities Wang et al. (2019) for a more robust financial system. Nonetheless, despite their improved accuracy, ML and DL models bring challenges

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such as overfitting Hastie et al. (2009), interpretability issues Lipton (2018), and the necessity for large datasets.

Building on this concept, this paper introduces the CLAM model to forecast the weekly trend of financial assets. CLAM is a hybrid deep learning architecture that combines stacked layers of **C**NN, **L**STM, and an **A**ttention **M**echanism (AM) to address the challenges identified in previous models. Our CLAM leverages CNNs for effective feature extraction, capturing spatial patterns in stock price data. LSTMs are then employed to manage temporal dependencies, effectively handling the sequence of data points over time. The attention mechanism further enhances the model by dynamically focusing on relevant features, allowing the model to prioritize critical information and mitigate the impact of less significant data. This combination of techniques enhances the model's ability to capture both short-term and long-term dependencies thus strengthening its robustness in handling non-linear relationships within the data. Nonetheless, recognizing the impracticality of forecasting stock price value, CLAM focuses on being a computationally efficient model by only focusing on equity movements, which is well-suited for real-time swing trading within volatile financial markets.

This paper is organized as follows: Section reviews financial forecasting literature, emphasizing the limitations of traditional models and advances in hybrid approaches. Section outlines the data processing, metrics, and the proposed CLAM architecture. Section describes the experimental setup, model comparisons, and performance results. Section discusses the findings and potential improvements. Finally, Section summarizes and suggests directions for real-time financial trading applications. CLAM is built on our previous research Anh et al. (2024); Anh and Ha (2024b,a).

Literature Review

Related Work

The stock market represents a complex system influenced by a wide range of often unrelated factors, such as psychological behavior and economic conditions. Among various forecasting models, the Back Propagation Neural Network (BP-NN) has been shown to outperform others, such as ARIMA and Random Forest Regression (RFR), in predicting the one-year stock prices of Chinese vaccine manufacturers Chen et al. (2015). This outcome is particularly beneficial for investors within the pharmaceutical sector. Additionally, a combination of Seasonal ARIMA and Extreme Gradient Boosting (SARIMA-XGBoost) has demonstrated impressive accuracy in forecasting the Indian Stock Index Mahajan and Sinha (2020), reflecting the potential of hybrid models in achieving high predictive performance. Similarly, the RFR model has been effective in predicting stock prices of companies listed on Indian exchanges, further indicating the utility of ML models in financial forecasting Bhuriya et al. (2017). These traditional ML approaches have proven effective, but the advent of Deep Learning, a subset of ML, has introduced a new level of precision in model development by autonomously learning hierarchical data representations LeCun et al. (2015). To advance stock market prediction, Wang et al. Wang et al. (2019) introduced a model that combines the LightGBM algorithm with wavelet packet decomposition (WPD) to filter out data noise before forecasting the Shanghai Composite Index. This hybrid approach successfully predicted the market trend over a 10-day period, surpassing the performance of ARIMA and Support Vector Regression (SVR) Wang et al. (2019). Furthermore, the integration of CNNs to enhance LSTM networks has led to major improvements in short-term prediction accuracy, showing a 25% increase on the CSI300 index Qin et al. (2017). A more advanced hybrid model, combining CNN, BiLSTM, and Efficient Channel Attention (ECA), showed strengths in predicting long-term trends by leveraging spatial and temporal data processing Zhang and Xu (2020).

Alternatively, combining LSTM and Gated Recurrent Unit (GRU) networks has yielded superior predictions of the S&P500 adjusted closing price, outperforming models that rely solely on GRU, LSTM, or Multilayer Perceptron (MLP) architectures Li et al. (2020). The success of these hybrid models underscores the importance of carefully engineered combinations, which can significantly enhance the precision and reliability of stock price forecasts Pang et al. (2020). Ultimately, constructing an effective forecasting model goes beyond selecting the most advanced architectures; it also requires the integration of appropriate mathematical and physical principles to analyze complex, chaotic systems that exhibit unpredictable and non-repetitive patterns due to their sensitivity to initial market conditions Mantegna and Stanley (1999). As a result, the inclusion of the Attention Mechanism (AM) has revolutionized the time series field Bahdanau et al. (2014). AM allows models to focus on the most relevant features within the data across multiple time intervals by selectively weighting the importance of different inputs. Hence, AM can improve the accuracy of predictions, especially in models like Transformers, where it serves as a core component Vaswani et al. (2017). Therefore, attention-based models and their variants Lim et al. (2021); Zhou et al. (2021) have advanced financial time series forecasting with their large multi-head attention mechanism.

Theoretical Background

Convolutional Neural Networks

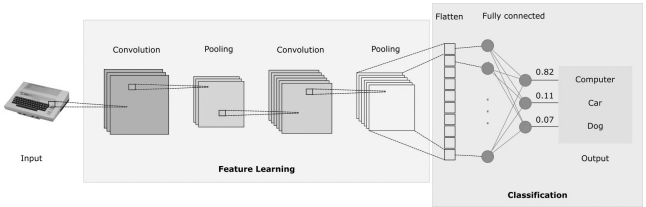


Figure 1. CNN architecture Shahriar (2021)

Convolutional Neural Networks (CNNs) were introduced as a type of feedforward neural network that excels in tasks such as image processing and natural language processing (NLP) Shahriar (2021). CNNs have also proven effective in time series prediction Wibawa et al. (2022). The ability of CNNs to utilize local connectivity and weight sharing reduces the number of parameters, leading to more efficient learning models. A typical CNN architecture consists of three primary components: convolutional layers, pooling layers, and fully connected layers Mann and

Kalidindi (2022). Each convolutional layer comprises multiple convolutional kernels, with the operation of these layers described by Equation (1). The convolutional layers extract features from the input data, but this often results in high-dimensional feature maps. Therefore, to address this thus decreasing the computational cost, pooling layers are employed after the convolutional layers to reduce the dimensionality of the features Zhao et al. (2024).

$$l_t = \tanh((x * k)_t + b_t) \tag{1}$$

In this equation, l_t represents the output at time step t after applying the convolution, $\tanh$ is the activation function, x is the input vector, k denotes the convolution kernel weights, and b_t is the bias associated with the convolution kernel. In addition, the convolution operation $(x * k)_t$ for a 1D input sequence can be expressed as:

$$(x * k)_t = \sum_{i=0}^{m-1} x_{t-i} \cdot k_i \tag{2}$$

Accordingly, m is the size of the kernel, x_{t-i} is the input at the i-th position relative to the current time step t, and k_i are the kernel weights at the i-th position.

Long Short-Term Memory

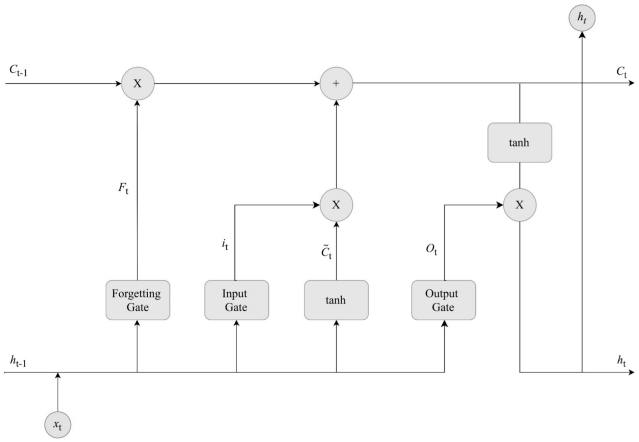


Figure 2. LSTM architecture

Long Short-Term Memory (LSTM), introduced by Schmidhuber et al. Hochreiter and Schmidhuber (1997b), was designed to address the challenges of gradient explosion and vanishing gradients in Recurrent Neural Networks (RNNs) Zucchet and Orvieto (2024). Unlike the standard RNN, which consists of a single repeating tanh module, LSTM includes four interactive components, making it more effective in capturing long-term dependencies Hochreiter and Schmidhuber (1997b). Accordingly, the core of LSTM is its memory cell, which is regulated by three gates: the forget gate, the input gate, and the output gate. These gates control the flow of information and update the cell state, which are outlined as follows:

1. The forget gate determines what portion of the previous cell state C_{t-1} should be retained, calculated as:
$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{3}$$
where σ is the activation function, W_f and b_f are the weights and bias of the forget gate, respectively.
2. The input gate updates the cell state with new information, determined by:
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$
$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{5}$$
where i_t is the input gate output, and $\tilde{C}_t$ is the candidate cell state.
3. The cell state C_t is updated by combining the forget gate and input gate:
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{6}$$
4. The output gate decides the next hidden state h_t by:
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$
5. Finally, the output of the LSTM is computed as:
$$h_t = o_t \cdot \tanh(C_t) \tag{8}$$

x_t represents the current input, h_{t-1} is the previous hidden state, and b terms denote biases for the respective gates.

Attention Mechanism

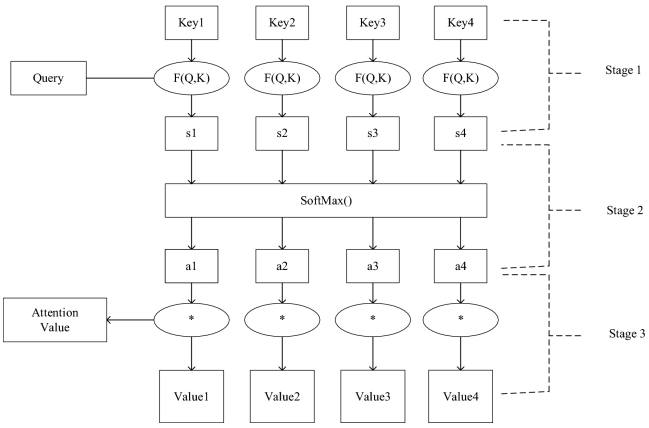


Figure 3. AM architecture Lu et al. (2020)

The Attention Mechanism (AM), introduced by Treisman et al. Treisman and Gelade (1980), optimizes models by focusing on the most relevant information within large datasets. By calculating the probability distribution of attention, AM highlights key inputs, effectively enhancing traditional models based on human visual attention principles. This mechanism prioritizes important information while disregarding less relevant details, thus efficiently allocating attention. The AM calculation process, as illustrated in Fig. 3, can be divided into three main stages:

1. The similarity between the Query (output feature) and Key (input feature) is calculated using:
$$s_t = \tanh(W_h h_t + b_h) \tag{9}$$
where W_h is the weight matrix, b_h is the bias vector of the attention mechanism, and h_t is the input vector (or Key) at time step t. This computes a raw score s_t, representing the similarity between the Query and Key.

2. The similarity score s_t is then normalized via the softmax function to obtain the attention weights:

$$a_t = \frac{\exp(s_t)}{\sum_{t'} \exp(s_{t'})} \tag{10}$$

Accordingly, a_t represents the attention weight for the input at time step t. The softmax function ensures that the attention weights form a probability distribution, where $\sum_t a_t = 1$. This step allows the model to assign higher weights to more relevant inputs.

3. The final attention value is calculated through a weighted summation over all the input vectors (or Values):

$$s = \sum_t a_t h_t \tag{11}$$

In equation 11, s is the context vector that aggregates the input information, with each input h_t weighted by its corresponding attention weight a_t, which is used in subsequent computations to make predictions.

Methodology

Data Collection and Evaluation Metrics

The OHLCV stock data, sourced from Yahoo Finance's S&P 500 Index, are categorized into two groups: Pharmaceuticals (AbbVie Inc., ABBV; Johnson & Johnson, JNJ) and Financials (Goldman Sachs Group Inc., GS; Citigroup Inc., C). This categorization is based on the fundamental differences between pharmaceutical companies and financial institutions, presenting a unique challenge for forecasting models. Pharmaceutical stocks are highly sensitive to abnormal events such as lab innovations, private research, and cure development, whereas financial stocks are more influenced by periodic events like political debates, fiscal policies, and human psychology. Additionally, CLAM employs a standard train-validate-test split ratio of 80:10:10. This means 80% of the data is used for initial training, 10% for validation and fine-tuning, and the remaining 10% for testing. The dataset's timeline is structured with a training period from July 19, 2004, to July 12, 2024 (20 years - 5,031 observations), followed by an out-of-sample forecast starting on July 13, 2024, predicting the next financial week. Consequently, the out-of-sample period spans July 15, 2024, to July 19, 2024 (5 observations).

The experiment concludes on July 20, 2024, ensuring that the data remains unseen during training to fully avoid the possibility of data leakage. The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are selected as evaluation metrics due to their effectiveness in identifying predictive errors in univariate analysis. MAE (12) provides the average magnitude of forecasting errors, serving as a straightforward measure of overall prediction accuracy, which is particularly crucial in the volatile stock market. RMSE (13), on the other hand, emphasizes larger errors, highlighting discrepancies that could have significant financial consequences. Mean Squared Error (MSE) is used as the loss function to measure the average squared difference between the predicted values and the actual target values, quantifying the model's prediction accuracy. Thus, greater errors indicate a larger deviation in price predictions.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i| \tag{12}$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{13}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{14}$$

Where:

n is the total number of data points or observations.

Y_i represents the actual (true) value of the stock price.

$\hat{Y}_i$ represents the predicted value of the stock price.

CLAM: CNN-LSTM-AM

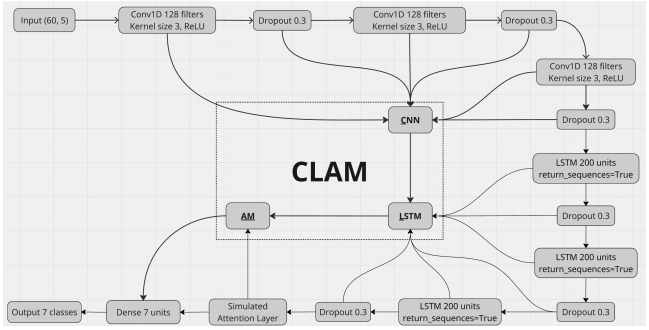


Figure 4. The proposed CLAM hybrid architecture

Table 1. Model architecture summary

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 60, 5)	0
conv1d (Conv1D)	(None, 60, 128)	2,048
dropout (Dropout)	(None, 60, 128)	0
conv1d_1 (Conv1D)	(None, 60, 128)	49,280
dropout_1 (Dropout)	(None, 60, 128)	0
conv1d_2 (Conv1D)	(None, 60, 128)	49,280
dropout_2 (Dropout)	(None, 60, 128)	0
lstm (LSTM)	(None, 60, 200)	263,200
dropout_3 (Dropout)	(None, 60, 200)	0
lstm_1 (LSTM)	(None, 60, 200)	320,800
dropout_4 (Dropout)	(None, 60, 200)	0
lstm_2 (LSTM)	(None, 60, 200)	320,800
dropout_5 (Dropout)	(None, 60, 200)	0
dense (Dense)	(None, 60, 1)	201
dense_1 (Dense)	(None, 60, 7)	14
Total params	1,005,623	
Trainable params	1,005,623	
Non-trainable params	0	

Concerning Fig. 4 and Table 1, the input data first passes through a series of convolutional layers, each employing 128 filters with a kernel size of 3, aimed at extracting intricate spatial features from the input sequence. The convolutional

layers are activated using the ReLU function, which aids in introducing non-linearity to the model while retaining computational efficiency. Dropout, applied at a rate of 0.3 after each convolutional layer, serves to prevent overfitting by randomly omitting a fraction of the neurons during training, thus enhancing the generalization capability of the model. Following the convolutional layers, the extracted features are fed into a sequence of LSTM layers. Each LSTM layer, consisting of 200 units, is designed to capture the temporal dynamics within the data by maintaining a memory of the previous time steps. The inclusion of multiple LSTM layers allows the model to build a hierarchical understanding of the temporal relationships. To further mitigate overfitting and improve model robustness, Dropout is consistently applied after each LSTM layer. A simulated Attention Mechanism is introduced after the LSTM layers, acting as a dense layer to approximate the focus on critical features across different time steps. This mechanism allows the model to prioritize the most relevant information for the forecasting task, enhancing its ability to capture dependencies that are crucial for accurate predictions.

Finally, the processed features are passed through a dense layer that outputs the forecasted values for the next 7 days. This dense layer represents the final synthesis of the model's learned features, mapping the encoded information to the predicted outcomes. The CLAM model's architecture (Fig. 4), showcases its capability to combine spatial, temporal, and attention mechanisms effectively. By employing a combination of CNNs, LSTMs, and a simulated AM, CLAM is well-equipped to handle the complex patterns inherent in sequential financial data, providing a robust framework for accurate time series forecasting. Dropout regularization is applied throughout the model, and an early stopping criterion ensures that the model remains both efficient and stable during the training process. These features contribute to the model's ability to generalize well to unseen data, thereby enhancing its utility in real-world applications.

Experiments and Results

Experimental Process

Our experimental procedure (Figure 5) began with the initialization of random number generators in both NumPy and TensorFlow libraries, ensuring consistency and reproducibility by setting a seed value of 42. The stock datasets, loaded from `csv` files, contained OHLCV data, which were first normalized to mitigate the effects of varying magnitudes within the features. Two separate `MinMaxScaler` instances were employed: one for the feature columns ("Open", "High", "Low", "Adj Close", "Volume") and another for the target column ("Close"). This normalization ensured the data was scaled uniformly, addressing potential biases and enhancing the model's performance by keeping values within the [-1, 1] range. Following normalization, sequences were constructed from the dataset, each with a length of 60 days to predict the subsequent 7-day closing prices. This sequence creation process, which produced numerous input-output pairs, was conducted exclusively on the normalized dataset, thereby preventing any leakage of future information. The sequences were subsequently split into training and validation sets, maintaining a 90:10 ratio to preserve the integrity of the experimental setup. Hence, this separation was crucial to evaluate the model on unseen data and prevent overfitting, preventing outsample forecast disruption.

The model architecture, a hybrid of convolutional and LSTM layers, was then defined to capture both spatial and temporal patterns inherent in the financial time series data. A batch size of 64 was selected for training, allowing for efficient processing of the data. Notably, an Attention layer was incorporated to dynamically weigh the input features, enabling the model to focus on more critical aspects of the data. The model was compiled using the Mean Squared Error (MSE) loss function and the Adam optimizer, supplemented by a learning rate scheduler (`ReduceLROnPlateau`), which reduced the learning rate by a factor of 0.2 if the validation loss did not improve for 5 consecutive epochs, with a minimum learning rate set at 0.001. An `EarlyStopping` callback was integrated, halting the training if the validation loss did not improve after 10 epochs, thus preventing overfitting and ensuring that the model generalized well. The architecture summary of the model was generated to provide an overview of the layers and parameters involved. Throughout training, the model iterated over the dataset in batches, updating the weights via backpropagation after each batch. The early stopping criterion was monitored using validation loss, and the model's state with the lowest validation loss was saved as the best model. Upon completing the training, the model was evaluated on the validation set, where it achieved an MAE and RMSE that provided insights into its predictive accuracy. Finally, the trained model was utilized to make out-sample forecasts, and the predictions were unscaled to facilitate a direct comparison with the test data.

Hyperparameter Tuning

Table 2. Hyperparameter tuning summary

Hyperparameter	Values Tested	Best Value
LSTM Units	100, 150, 200	200
Conv1D Filters	64, 128, 256	128
Kernel Size	3, 5, 7	3
Dropout Rate	0.2, 0.3, 0.4	0.3
Batch Size	32, 64, 128	64
Learning Rate	0.01, 0.005, 0.001	0.001
Optimizer	Adam, RMSprop, SGD	Adam

As illustrated in Table 2, a wide spectrum of values was tested across essential hyperparameters, including LSTM units, Conv1D filters, kernel size, dropout rate, batch size, learning rate, and optimizer selection. This exhaustive tuning process was essential to strike the delicate balance between model complexity and generalization, with a specific focus on avoiding overfitting, a common pitfall in deep learning models. The selection of 200 LSTM units, for instance, was the result of a careful trade-off. While a smaller number of units (such as 100 or 150) led to faster convergence, these configurations consistently underperformed in capturing the complexity of the sequential data, as evidenced by higher validation errors.

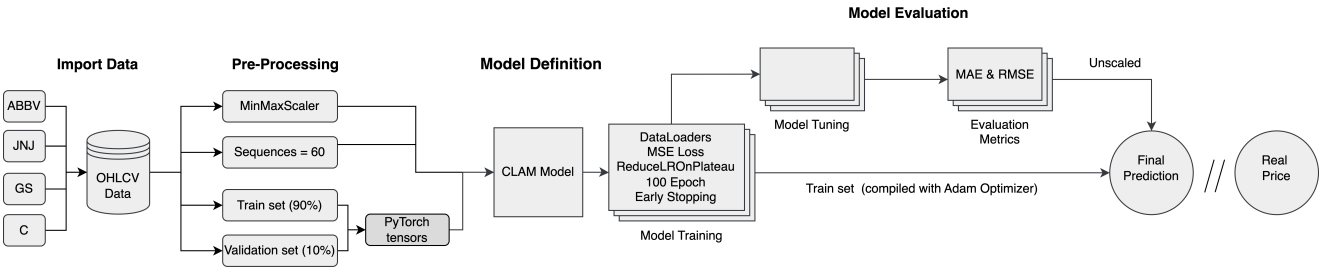


Figure 5. Full experimental process

Conversely, larger configurations, such as 256 Conv1D filters, introduced unnecessary computational overhead without a commensurate improvement in performance, highlighting the diminishing returns of increasing model depth and width. In addition, the kernel size of 3 was particularly effective in capturing localized temporal patterns, contrasting with larger kernels that diluted the model's ability to focus on fine-grained features.

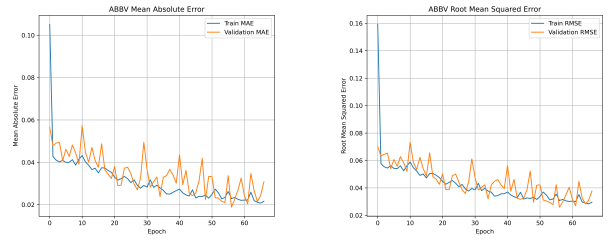
Moreover, the dropout rate of 0.3 was determined to be optimal after observing that lower rates led to overfitting, while higher rates hindered learning, reducing the model's capacity to generalize. The choice of a batch size of 64 was similarly contrasted against smaller and larger batch sizes, where smaller batches resulted in noisier gradient estimates and larger batches slowed down the training without significant gains in accuracy. The learning rate of 0.001, coupled with the Adam optimizer, offered the best balance between learning speed and stability, particularly when compared to other optimizers like RMSprop and SGD, which either converged slower or required more tuning.

Performance Comparison

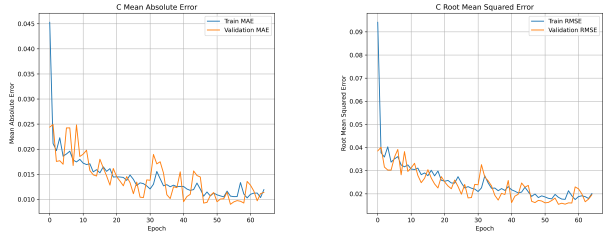
The performance evaluation in Table 3 clearly identifies the CLAM model as the superior performer, with the LSTM-AM model securing the second position. CLAM's validation MAE of 0.007 on the ABBV dataset is a remarkable 91.8% improvement over the 0.085 recorded by LSTM-AM, which itself is 16.7% better than CNN-LSTM's 0.102. This substantial reduction in error demonstrates CLAM's advanced capability in capturing complex temporal dependencies more effectively than the other models. In contrast, while LSTM-AM's attention mechanism allows it to surpass CNN-LSTM and other models, reducing the MAE by 34.4% compared to CNN's 0.115, it still lags significantly behind CLAM, underscoring the latter's superior architecture and precision. Further emphasizing CLAM's dominance, the validation RMSE figures show a similar pattern. CLAM achieves a validation RMSE of just 0.012 on ABBV, representing an 89.4% reduction compared to LSTM-AM's 0.113, and an even more striking 91.5% decrease compared to CNN's 0.142. LSTM-AM, while effective, reduces the RMSE by 11.7% compared to CNN-LSTM's 0.128, but this improvement pales in comparison to the nearly perfect generalization displayed by CLAM. The consistency of CLAM's performance across both MAE and RMSE, with such substantial percentage reductions, clearly positions it as the best model, with LSTM-AM as a commendable yet significantly less effective second choice.

CLAM Inspection

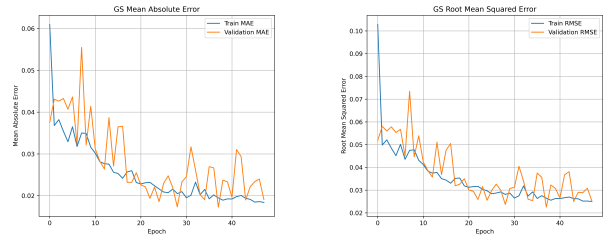
Training and Validation



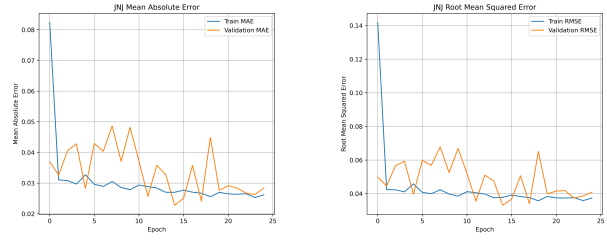
(a) MAE of ABBV **(b)** RMSE of ABBV



(c) MAE of C **(d)** RMSE of C



(e) MAE of GS **(f)** RMSE of GS



(g) MAE of JNJ **(h)** RMSE of JNJ

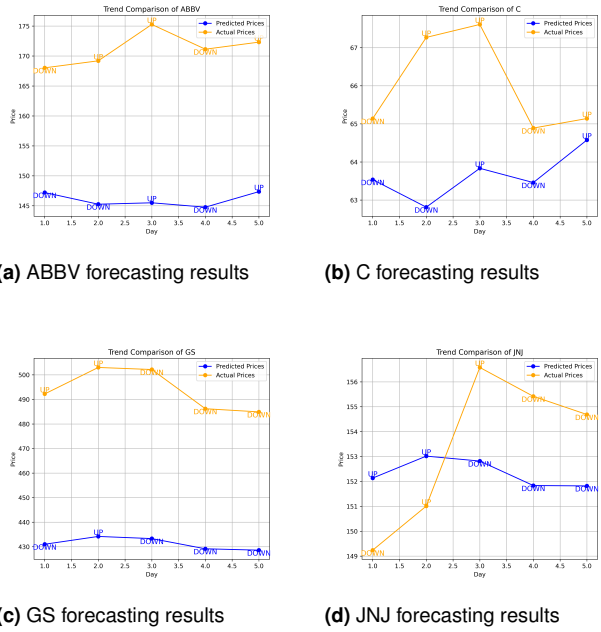
Figure 6. Summary of MAE and RMSE for different datasets

Table 3. Model performance on train and test sets

Model	ABBV		C		GS		JNJ	
	Train	Test	Train	Test	Train	Test	Train	Test
MAE								
CNN Akehýr and Kılıç (2022)	0.112	0.115	0.138	0.135	0.129	0.131	0.102	0.108
LSTM Al-Utaibi et al. (2023)	0.124	0.128	0.148	0.151	0.153	0.156	0.125	0.131
CNN-LSTM et al. (2022)	0.096	0.102	0.105	0.110	0.098	0.106	0.093	0.100
LSTM-AM Chen et al. (2023)	0.080	0.085	0.092	0.096	0.089	0.093	0.081	0.088
CLAM	0.018	0.007	0.011	0.018	0.016	0.022	0.031	0.017
RMSE								
CNN Akehýr and Kılıç (2022)	0.137	0.142	0.185	0.184	0.174	0.177	0.129	0.137
LSTM Al-Utaibi et al. (2023)	0.158	0.161	0.190	0.195	0.199	0.202	0.160	0.167
CNN-LSTM et al. (2022)	0.121	0.128	0.139	0.143	0.131	0.140	0.120	0.128
LSTM-AM Chen et al. (2023)	0.106	0.113	0.125	0.129	0.118	0.125	0.110	0.116
CLAM	0.025	0.033	0.019	0.025	0.022	0.033	0.025	0.024

The training process (Fig. 6) for ABBV shows effective learning, with MAE dropping from 0.10 to 0.025 by epoch 20, and validation MAE stabilizing around 0.025 by epoch 65. RMSE decreases from 0.16 to below 0.04, indicating strong generalization. For stock C, the training MAE quickly declines from 0.045 to 0.020 by epoch 10, while validation MAE stabilizes around 0.015 by epoch 30. Both MAE and RMSE converge near 0.010 and 0.02, respectively, by epoch 60, reflecting robust learning. In GS, training MAE drops to 0.03 by epoch 10, with validation MAE stabilizing at 0.02 by epoch 30. RMSE similarly decreases below 0.03, confirming effective model performance. For JNJ, the training MAE drops to 0.03 by epoch 5, with validation MAE stabilizing around 0.03 by epoch 10. RMSE decreases to 0.04 from epoch 10 onward, showing effective learning dynamics.

Trend Forecasting



(a) ABBV forecasting results **(b)** C forecasting results

(c) GS forecasting results **(d)** JNJ forecasting results

Figure 7. Forecasting results for different datasets

Finally, CLAM is deployed into real-world scenarios for outsample forecasting generation (Fig. 7), then contrasted with the end-period value. By leveraging historical price patterns, CLAM aims to capture shifts in market momentum, labeling trends as "UP" if the next day's price is expected to rise and "DOWN" if it is expected to fall. This approach reduces the influence of short-term noise.

For ABBV, CLAM successfully identified the immediate downtrend on Day 1 (Monday), a day typically marked by high volatility and investor reactions post-weekend. Although it initially missed the recovery on Day 2, it adjusted and accurately predicted the upward trend on Day 3. CLAM then continued to forecast the correct trend for the final two days, resulting in three consecutive accurate predictions and capturing the overall uptrend of ABBV, achieving an accuracy of 80%. In the case of C, CLAM once again identified the initial downtrend on Monday but failed to predict the following day's trend. However, it redeemed by precisely forecasting the trend for the last three days consecutively, with minimal price deviation, leading to an overall accuracy of 80%. Concerning GS's case, despite missing the initial rise on Day 1 (after the weekend), CLAM consistently predicted the correct trend for the remaining four consecutive days, successfully capturing the overall downtrend for the week and once again achieving 80% accuracy. Finally, for JNJ, while CLAM effectively captured the overall downward trend, it struggled with consistency, failing to predict the trends on Days 1 and 3. Nevertheless, it accurately captures the sharp decline in the final two days, resulting in a 60% accuracy for JNJ.

Overall, CLAM achieved an average trend forecasting accuracy of 75% across pharmaceutical and finance stocks. The model demonstrated strong performance in most cases, particularly in forecasting consecutive trends, and identifying immediate downtrends.

Discussion

Summary of Findings and Contributions

Our research demonstrates that the integration of stacked deep learning layers in the CLAM model—comprising

Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Attention Mechanisms (AM). CLAM significantly outperforms traditional standalone models. This superiority is attributed to CLAM's advanced feature extraction and attention mechanisms, which enhance the LSTM architecture's inherent ability to capture long-term dependencies in time series forecasting. As a result, CLAM achieves an average reduction of over 80% in MAE and RMSE compared to conventional models such as CNN, LSTM, CNN-LSTM, and LSTM-AM. Additionally, our experiments indicate that in 3 out of 4 cases, CLAM successfully forecasts the correct trends for 3-4 consecutive days, effectively capturing market downturns on the opening day, which tends to be unpredictable due to abnormal traders' behavior.

Finally, CLAM achieves a 75% accuracy rate in stock trend forecasting. This highlights the potential of hybrid models in time series forecasting, demonstrating that attention-based deep learning hybrids like CLAM are particularly well-suited as live-trading indicators for investors focused on weekly trends. Hence, CLAM enhances decision-making processes in financial trading, providing a robust and lightweight tool for forecasting short-term financial market movements.

Limitations and Recommendations

Our study is grounded in raw OHLCV data of stock prices, which offers ease of access but also introduces potential market biases. This limitation arises from the model's inability to account for external economic or financial factors, such as extreme events, technical indicators, or government policies, all of which are crucial drivers of stock prices. Additionally, since our research primarily focuses on trend detection, the CLAM architecture is not fully optimized for value trading, where precise price gaps are critical. As a result, CLAM's potential may extend further and be more robust than demonstrated in its current form. We encourage researchers to expand upon our work by developing deeper hybrid models or employing explainable models to study stock trends effectively. In addition, practitioners are advised to enhance data collection processes by incorporating data from stock indexes and integrating relevant technical trading indicators, thereby uncovering more intricate stock patterns within the raw target features.

Conclusion

This study introduced the CLAM model, a novel hybrid combination of Convolutional Neural Networks, Long Short-Term Memory networks, and Attention Mechanisms designed for multi-step stock price trend forecasting. The model demonstrated significant improvements in predictive accuracy, with an average reduction of over 80% in MAE and RMSE compared to traditional models. CLAM's ability to effectively capture complex temporal dependencies and its robust performance across various stock datasets highlight its potential as a valuable tool in financial forecasting. The findings of this research suggest that CLAM is particularly well-suited for short-term trend forecasting, providing accurate and timely predictions that can assist investors and traders in making informed decisions.

The model's design, which integrates feature extraction and attention mechanisms, offers a significant advancement over existing approaches. Moreover, there are several promising directions for further research. Future studies could explore enhancing CLAM's adaptability to different market conditions, such as varying levels of market volatility or the impact of external economic factors. Integrating CLAM with other financial analysis techniques, such as sentiment analysis or candlestick pattern recognition, could also improve its predictive capabilities. Real-time deployment of CLAM in live trading environments of daily stocks or hourly cryptocurrency prices is another area that warrants investigation for real-time performance assessment.

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