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An automatic stock price movement prediction using circularly dilated convolutions with orthogonal gated recurrent unit

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ABSTRACT

Recently, stock trend analysis has played an integral role in gaining knowledge about trading policy and determining stock intrinsic patterns. Several conventional studies reported stock trend prediction analysis but failed to obtain better performance due to poor generalization capability and high gradient vanishing problems. In light of the need to forecast stock price trends using both textual and empirical price data, this research proposed a novel hybridized deep learning (DL) model. Preprocessing, feature extraction, and prediction are the three effective stages that the created research goes through in order to properly estimate the stock movements. Data cleaning, which helps improve data quality, is calculated in the preprocessing step. Next, we use the created CDConv-OGRU technique-hybridized circularly dilated convolutions with orthogonal gated recurrent units-to extract features and make predictions. Python serves as the platform for processing and analyzing the created approach. This research uses a publicly accessible StockNet database for testing and compares results using a number of performance metrics, including accuracy, recall, precision, Mathew's correlation coefficient (MCC), and f-score. In the experimental part, the created approach obtains a total of 95.16% accuracy, 94.8% precision, 94.89% recall, 95% confidence interval, and 0.9 MCC, in that order.

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1. INTRODUCTION

At present, stock movement prediction become a more challenging problem in the field of financial engineering because of its increased financial reimbursements [1]. However, determining the stock movements is not an easy task as it is highly non-linear and randomly dependent. In day today life, predicting stock trends become the hot research topic because of its effectiveness in financial applications any existing studies utilized time series prediction schemes based on empirical price information [2]. Due to technological advancements, text collected from online social media platforms has gained much attention from the investors to determine the stock trends accurately [3]. The text data contains the public opinions of the investors as well as other expert ideas that can create great impact among the trading investors [2].

Several past studies considered empirical price information that cannot provide accurate prediction performance while compared with text information. Hence, many models utilize both text and empirical price information to enhance the performance in stock movement prediction process [4]. Moreover, if the company is suffered from high outrages on a particular trading, its stock price reduces on the upcoming trading days. The downtrend patterns can be determined by the investors helps to predict the stock movements during each trading days. This historical dependence is due to that the information requires more time to determine the stocks movements effectively. Some traditional techniques combine empirical price and text data to determine the stock movements based on discriminative and procreative techniques [5].

The discriminative techniques utilize data to understand a resultant function for prediction process. The procreative techniques define the hidden variables obtained from the observed data based on particular attributes. The procreative techniques can explain the generative process accurately for handling the market non-linearity. Recent developments in procreative methods have made it easier to improve procreative model performance by extracting characteristics from complicated datasets. Nevertheless, owing to issues with high gradient vanishing during training, stock movement prediction networks such as StockNet have weak generalization capabilities. As a result, the performance accuracy of the models used to forecast stock movement was decreased to a certain amount. An unique hybridized deep learning (DL) model for forecasting stock movements based on text and historical price information was presented in the produced research to handle this problem.

Driving force: Because stock investors rely on accurate stock price movement predictions to generate income all year round, this area of study has recently exploded in popularity. The intricate patterns and inherent unpredictability of stock prices make it difficult to forecast daily trading-based stock price fluctuations. In the past, researchers have relied on a number of labor-intensive manual procedures that have been unable to establish a correlation between price and financial news. Therefore, in order to help stock investors successfully identify the forthcoming stock changes, we need methodologies that improve prediction performance. New DL models understand financial stock trends properly, which improves performance while reducing mistake and time consumption. This is the driving force for the study's new hybridized DL model, which assesses stock price aspects using an improved feature learning procedure. Here are the main points of the research that was developed:

- To provide a novel hybridized DL method for forecasting stock movements utilizing text and empirical price information, CDConv-OGRU.
- To clean up the text and empirical pricing data during the preparation phase to make them more reliable.

The goals of this study are two-fold: first, to suggest a novel method for predicting stock trend movements using a hybrid of circularly dilated convolutions and orthogonal gated recurrent units (CDConv-OGRU); and second, to compare the results of this study to those of more conventional approaches by computing key performance indicators such as recall, accuracy, precision, mathematics correlation coefficient (MCC), and F-measure.

In section 2, we examine the research on DL-based stock movement prediction and provide our interpretations. In section 3 details the approach that was created. The findings and analysis are presented in section 4. The study's conclusion is presented in section 5.

2. RELATED WORKS

Accurate stock price determination was shown by Ma *et al.* [6] using an aggregated categorization technique. This study established bidirectional long short-term memory (Bi-LSTM), or bidirectional long short-term memory, to forecast stock price changes. Graph convolutional networks (GCNs) equipped with market sentiment classifier (MSC) modules were used for feature extraction. About 54,900 news titles covering the period from January 2, 2018, to June 18, 2021 make up the Chinese stock market in the simulation. In the end, we compared our results to those of previous research using a number of metrics, including accuracy and MCC. Nonetheless, the temporal complexity of analyzing the financial news provided in the dataset is raised by this strategy.

To analyze stock movements based on sentiment and news trends, Daradkeh [7] proposed hybrid DL frameworks. To reliably forecast stock market patterns, this research used a convolutional neural network with Bi-LSTM (CNN-Bi-LSTM). From January 1, 2020, through December 1, 2021, researchers used data from the Dubai Financial Market (DFM) database, which includes news and sentiment aspects. In the end, we compared our results to those of previous research using a number of metrics, including precision, sensitivity, accuracy, and F-measure. The method's significant data disappearing difficulties prevented it from evaluating the different trading cycles for forecasting market movements, however.

To improve sentiment-based stock movement prediction, Huang *et al.* [8] presented the improved DL model. The authors of this study successfully predicted future stock market movements by combining LSTM with a genetic algorithm (GA). On top of that, we used five different sentiment variables to examine stock price movements, and we calculated the grey relational analysis (GRA) to see how sentiment patterns relate to stock prices. The modeling technique made use of the TSMC dataset, which includes 561 trading days before to the epidemic and 290 trading days after it had passed. In the experimental setting, we compared our method's accuracy before and after the pandemic to that of other approaches. This approach may have performed better overall, but it still can't hold its own when dealing with datasets that are much bigger.

The stock movement prediction was achieved by Pandikumar *et al.* [9] by the use of an effective DL model. Here, we present the LSTM recurrent neural network (RNN) method for stock movement prediction under intraday trading circumstances. This research used a publicly accessible stock dataset from State Bank of India (SBI) that includes several data parameters such as open, close, high, low, and volume. The evaluation section included a comparison of previous research with respect to accuracy, mean square error (MSE), and mean absolute percentage error (MAPE). Nevertheless, this approach does not solve the issue of data duplication and results in high gradient vanishing during training.

For the purpose of making stock price predictions using market and price history, Leng *et al.* [10] developed the DL model. To successfully forecast changes in stock prices, this research used the variational autoencoder (VAE) method and the gated orthogonal recurrent unit (GORU). Here, GORU is used to encode the text data, and VAE is used to decode the market data, which is then combined with the stock price data. In order to train, we used two open-source databases: StockNet and Astock. Lastly, other metrics were examined and differentiated from previous research, including precision, accuracy, recall, F-measure, and MCC. Unfortunately, the learned parameters aren't really ideal, therefore this approach uses a lot of memory. A number of generative models have been used for trend forecasting in the market in prior years. These include VAE [11] and Bayesian networks [12], [13]. Foretelling market tendencies in the future, Bayesian network-based models employ the distribution of stock data from the past. Models using these parameters have shown lower values for the correlation coefficient and root mean square error (RMSE). Compared to Bayesian networks, VAE [14] does a better job of reasoning and learning when given large data sets and a difficult posterior distribution. Luo *et al.* [15] proposed a VAE-based stochastic volatility model to improve the accuracy of assessing the time dynamics of stock volatility. Nevertheless, due to their reliance on simple discrete data for stock change forecasting, these models have difficulty understanding the interconnectedness of data across time. In addition, the stock prediction issue is transformed into an optimization problem by scientists who use optimization algorithms [16]-[20], such as aquila optimizer [21], arithmetic optimization algorithm [22], sine cosine algorithm [23], and whale optimization algorithm [24], to forecast market movements. Machine learning can handle vast datasets and find intricate patterns, it has gained popularity as a method for predicting fluctuations in stock prices. Nevertheless, there are still a number of research gaps in this area despite the achievements.

2.1. Data preparation and quality

Noise and outliers: these two factors can have a big influence on the performance of a model and are frequently present in financial data. Creating reliable methods to deal with noisy data is still difficult.

Engineering features: research is continually being done to find and develop pertinent elements that can increase prediction accuracy. Investigating novel financial indicators, sentiment analysis, and alternative data sources (such as social media and news articles) are some examples of this.

2.2. Explainability and interpretability of the model

Unboxed models: it can be challenging to comprehend the predictions of many machine learning models, particularly DL models, since they are regarded as "black boxes." It is essential to develop strategies to improve these models' interpretability and explainability.

Causality: it is difficult to understand and frequently ignored how different variables affect stock price movements. More accurate predictions might come from research on combining machine learning models with causal inference.

2.3. Algorithmic enhancements

Hybrid models: by combining many model types (such as statistics and machine learning models), prediction accuracy may be increased. The best practices for integrating these models are still being researched.

Group techniques: while it is well recognized that using ensemble approaches improves performance, it is still difficult to determine which models work best together and to fully grasp each member's individual contributions.

2.4. Predictiveness in real time and scalability

Latency and efficiency: accurate models that are also computationally and latency-efficient are necessary for real-time prediction. Creating scalable models with real-time streaming data handling capabilities is a key field of research.

Deployment: More study into resource management and model optimization is necessary for the effective deployment of machine learning models in production settings, particularly in high-frequency trading.

2.5. Risk control and sturdiness

By filling in these research gaps, machine learning models for predicting stock price movement can become more precise, dependable, and understandable, which will ultimately improve financial market decision-making.

3. PROBLEM STATEMENT

A number of limitations in forecasting stock price fluctuations have been identified by a comprehensive review of the relevant literature. Due to non-linear, complicated, and unpredictable patterns in the stock movement data, the most typical downside is poor accuracy and high gradient vanishing difficulties. In order to find the link between investors' empirical price knowledge and the impending stock price, several research encounter significant training times. Nowadays, stock investors are able to make more accurate predictions about the future movements of stocks because to the role that artificial intelligence (AI) technology plays in the financial industry. As a result, DL models powered by AI automatically link extensive text data with empirical price information to ascertain stock movements according to investors' trading days. This project aims to construct efficient hybridized DL models that can learn stock features and forecast price movements. Developed research exceeds greater performance in forecasting stock trend movement and overcomes all limitations experienced by previous studies, as far as we are aware.

4. DEVELOPED METHODOLOGY

In order for stock investors to reap financial rewards in the future, stock price prediction has recently assumed a vital role. The intricate patterns and inherent unpredictability of stock prices make it difficult to forecast daily trading-based stock price fluctuations. Therefore, in order to forecast stock price trends utilizing text and actual price data, this work suggests a novel hybridized DL model.

In order to properly estimate the stock movements, the produced research goes through three effective stages: pre-processing, feature extraction, and prediction. The developed study's procedure is shown in Figure 1. Data cleaning is a computation that helps improve data quality and is done at the pre-processing step. The next step is to use the newly-developed hybridized CDConv-OGRU method to extract features and make predictions. The created method is run via the python simulation platform for processing and analysis. Using the publicly accessible StockNet database as an experimental set-up, this research computes and compares a number of performance metrics, including accuracy, recall, precision, MCC, and f-score.

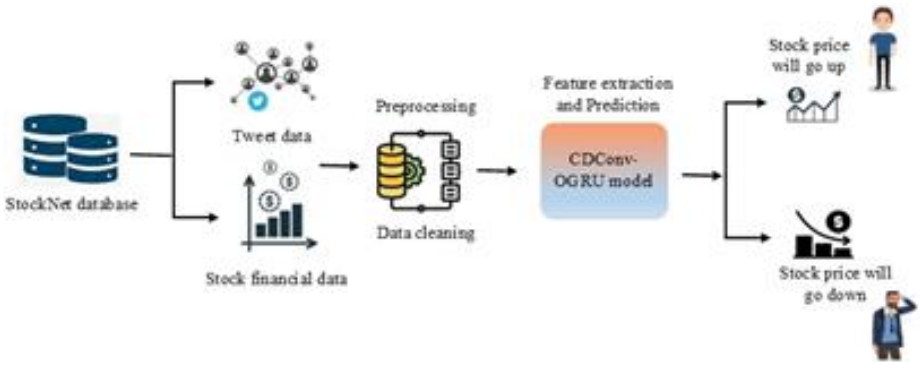

Figure 1. Workflow of the developed study

4.1. Preprocessing

High levels of noise, missing numbers, and data redundancy are all issues with the database's raw data. The data cleaning procedure is implemented at the beginning of the process to improve the data quality and address this problem. Finding and removing damaged or missing values from the database is the first step in the data cleaning process. The accuracy performance and prevention of data redundancy concerns are both enhanced by this technique. By adopting a data purification procedure, we may also reduce the overfitting difficulties and undesired training complications.

4.2. Feature extraction and prediction using CDConv-OGRU technique

After data cleaning process, feature extraction and prediction are done to determine the rise or fall in stock trends efficiently. For performing this, the present study introduced an innovative hybridized CDConv-OGRU technique that process the features and improve prediction accuracy in determining stock trends. The developed OGRU model consist of two components namely market information (MI) encoder and stock movement (SM) decoder. In addition to this, the CDConv technique learns the stock movements based on trading days during delay period to enhance the prediction performance.

The actual trading days are cleaned to obtain the trading days under non-holiday and non-weekend conditions (s_1, s_t) where $t \in (1, \ldots T)$. Let us assume that the SM x_t of stock z on a trading time s_t is exaggerated by SM X' based on the existing t' trading days. For enhancing the prediction performance, the stock trend x_t prediction on the trading time s_t as well as trading on $(s_{t-t'+1}, s_t)$ time are also considered. In this study, the delay time is determined as the term $(s_{t-t'+1}, s_t)$.

4.2.1. OGRU

The OGRU alters the recurrent matrices into orthogonal matrices and modReLU activation function (AF) is utilized for updating the hidden state representations. The mathematical expression for upgrading the OGRU hidden states are depicte:

$$H_t = H_{t-1}\Theta J_t + (1 - J_t)\Theta\, modRe\,LU\left(W_y y_t + i_t \Theta(Z H_{t-1}) + Bias_H\right) \tag{1}$$

$$J_t = \sigma\left(W_J H_{t-1} + W_{J,y} y_t + Bias_J\right) \tag{2}$$

$$i_t = \sigma\left(W_i H_{t-1} + W_{i,y} y_t + Bias_i\right) \tag{3}$$

Here, Θ indicates the element multiplication, σ represents the non-linear AF, W_J, and W_i indicates the weight matrices of reset and update gates, $W_{J,y}$ and $W_{i,y}$ manipulates the weight matrices and Z indicates the orthogonal matrix. Figure 2 indicates the architecture of CDConv-OGRU technique.

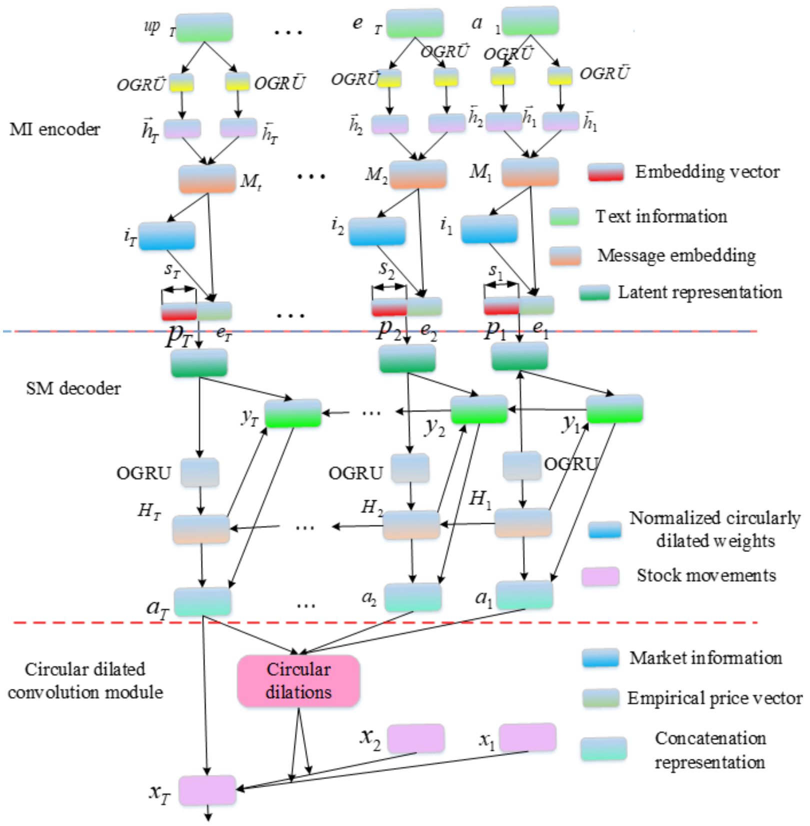

Figure 2. Architecture of CDConv-OGRU technique

4.2.2. MI encoder

It utilizes OGRU technique to encode the news events up_t at the time of (s_{t-1}, s_t) to produce the embedding vector p_t. The empirical price vector e_t is determined by stabilizing the empirical price information ue_t based on s_{t-1}. Using forward and backward OGRUs, the text information is encoded and it is mathematically formulated as (4)-(6).

$$\vec{h}_f = OGR\vec{U}(w_f, \vec{h}_{f-1}) \tag{4}$$

$$\overleftarrow{h}_b = OGR\overleftarrow{U}(w_b, \overleftarrow{h}_{b+1}) \tag{5}$$

$$M_t = (\vec{h}_{d'} + \overleftarrow{h}_{d'})/2 \tag{6}$$

Here, $f \in (1, \ldots d')$, $b \in (1, \ldots d')$, w_f, $w_b \in (w_{1,} w_2, \ldots \ldots w_D)$ and $. d' \in (1, . D)$ indicates the word location related to stock. The hidden values $\vec{h}_{d'}, \overleftarrow{h}_{d'}$ are summed up to determine the message embedding vector M_t. Because of varying discrepancies of the financial news events, the stock trend prediction also gets varied. Hence, the weights the news information are normalized and it can be mathematically formulated as (7).

$$v_t = \beta(l_v^T \, tanh(L_{M,v} N_t)) \tag{7}$$

Here, $\beta(.)$ indicates the SoftMax function where $L_{M,v} N_t$ represents the network parameters. Finally, the input for the text embedding vector p_t can be mathematically formulated as (8).

$$p_t = N_t v_t^T \tag{8}$$

Let us assume the actual price $e_t' = (e'^c_t, e'^h_t, e'^l_t)$ where, e'^c_t, e'^h_t and e'^l_t indicates the closing price, highest price and lowest price respectively. For predicting the stock movements, the actual price e_t' is normalized to obtain $e_t = e_t'/e'^c_{t-1}$ whereas e'^c_{t-1} represents s_{t-1} closing price. At last, the parameter p_t is combined with e_t to produce MI Y and it can be formulated as (9).

$$y_t = (p_t, e_t) \tag{9}$$

4.2.3. SM decoder

The SM decoder runs iteratively so that the latent factor $\mu$and the stock trend X are decoded from the encoded MI Y. The prediction outcome $p_\varpi = (X, \mu|Y)$ is similar to the stock trend prediction $X = (x_t, \ldots x_T)$ and it can express as (10).

$$p_\varpi(X, \mu|Y) = p_\varpi(x_T|Y, \mu) p_\varpi(\mu_t|\mu_{<t}) = \prod_{t=1}^{T-1} p_\varpi(x_t|y_{<t}\mu_t) \, p_\varpi(\mu_t|\mu_{<t}, y_{<t}, x_t) \tag{10}$$

Here, $p_\varpi(\mu_t|\mu_{<t}, y_{<t}, x_t)$ represents the actual posterior density and it is inflexible. Hence, the variational approximation $q_\varpi(\mu_t|\mu_{<t}, y_{<t}, x_t)$ is performed to maintain flexible outcomes. Finally, the OGRU technique is utilized to decode the MI and it can be formulated as (11).

$$h_t^z = OGRU(y_t, h_{t-1}^z) \tag{11}$$

Here, h_t^zindicates the hidden MI and the shared hidden demonstration h_t^μcan be formulated as (12).

$$h_t^\mu = tanh(W_\mu^\theta(\mu_{t-1}, y_t, h_t^z) + B_\mu^\theta) \tag{12}$$

Here, W_μ^θ indicates the weight matrix and B_μ^θ indicates the bias function. Because of gaussian distributions, μ_t can be reformulated as (13).

$$\mu_t = s_t + \gamma_t \Theta \alpha \tag{13}$$

Here, Θ represents the element-wise multiplication and α indicates the noise term involved in the developed model. The final prediction outcome can be mathematically formulated as (14) and (15).

$$a_t = tanh(W_a[y_t, h_t^z, \mu_t] + B_a) \tag{14}$$

$$x_t = \beta(W_x a_t + B_x), t < T \tag{15}$$

Here, W_a, W_x indicates the weight matrices and B_a, B_x indicates the bias function.

4.2.4. CD convolution model

This method considers the stock movements $X' = (x_t, \ldots\ldots x_{T-1})$ of the trading time during delay period as the prediction assistance for determining stock movement $x_T$of the outcome trading day. The circular dilation evaluates their weights by considering two elements namely dependency score (DS) $\tilde{e}_u$ and information score (IS)$\tilde{e}_j$. It can be mathematically formulated as (16)-(18).

$$\tilde{e}_j = w_j^T \, tanh\left(W_{a,j} G'\right) \tag{16}$$

$$\tilde{e}_u = a_T^T \, tanh\left(W_{a,u} A'\right) \tag{17}$$

$$e *= \beta\left(\tilde{e}_j \Theta \tilde{e}_u\right) \tag{18}$$

Here, $\beta(..)$ indicates the softmax function, $W_{a,j}$ and $W_{a,u}$ indicates the model parameters. The IS $\tilde{e}_j$ contains the amount of empirical trading days and the DS $\tilde{e}_u$ contains the correlated time between important stock patterns and empirical trading data. In addition to this, a_T indicates the outcome representation of the MI. Finally, the outcome stock trend prediction a_T is obtained by evaluating X' and a_T is depicted (19).

$$a_T = \beta(W_T(X' e *^T, a_T) + bias_T) \tag{19}$$

Here, W_T indicates the weight matrix. Finally, the stock movements are predicted accurately using the developed study using useful stock patterns.

5. RESULTS AND DISCUSSION

The developed study is simulated with the Python platform and several assessment measures like accuracy, MCC, F-measure, precision, and recall are analyzed and compared with other conventional studies. For the simulation process, StockNet database [11] is considered that consists empirical price information of 88 stocks collected from 1st January 2014 to 1st January 2016. In addition to this, the news events from nine industries are taken from the twitter social media platform. For training process, information between 1st January 2014 and 1st August 2015 are considered. For validation process, the information from 2nd August 2015 to 30th September 2015 are considered. For testing process, the data from 1st October 2015 to 1st January 2016 are considered.

5.1. Assessment measures

$$Acc(\%) = \frac{w+x}{w+x+y+z} \times 100\% \tag{20}$$

$$MCC = \frac{x \times w - z \times y}{\sqrt{(x+z)(x+y)(w+z)(w+y)}} \tag{21}$$

$$Pr\,e\,(\%) = \frac{x}{x+z} \times 100\% \tag{22}$$

$$rec(\%) = \frac{x}{x+y} \times 100\% \tag{23}$$

$$F - score(\%) = 2 \times \frac{Pr\,e \times Sen}{Pr\,e + Sen} \times 100\% \tag{24}$$

Here, w, x, y, $z$indicates the true negative (TN), true positive (TP), false negative (FN), and false positive (FP) respectively.

5.2. Comparative analysis of developed study over conventional techniques

In this subdivision, the performance obtained by the developed method over the existing methods is analyzed via various performance measures like accuracy, recall, precision, F-measure and MCC metrics. To prove the efficiency of the developed method, the performances of several existing methods like random (Rand) prediction, autoregressive integrated moving average (ARIMA), support vector regression (SVR), LSTM, GRU, gated orthogonal recurrent unit with VAE (GORU-VAE), hybrid attention network (HAN) [10] are also determined.

Table 1 indicates the performance analysis of developed study over existing studies. Form the tabulation, it is obvious that the developed study obtained outstanding performance in predicting the stock trend movements effectively. The developed study learns the stock patterns accurately and maintain high correlation between news events and empirical price information to achieve better accuracy performance. The prediction of stock price movement has been greatly impacted by machine learning since it has made sophisticated tools and techniques for analyzing intricate financial data available. The main effects listed below are felt. A detailed analysis of the comparative performances is depicted.

Table 1. Performance analysis of developed study over existing studies

Performance measures	Rand	ARIMA	SVR	LSTM	GRU	GORU+VAE	HAN	Developed study
Accuracy (%)	49.1	49.3	50.8	50.9	50.6	57	52.8	95.16
Precision (%)	56.2	56.9	55.4	49.7	49.4	57.7	55.2	94.8
Recall (%)	35.5	40.2	53.3	75.9	75.9	96	88.3	94.89
F-measure (%)	43.5	47.1	54.4	60.1	59.9	72.1	67.6	95
MCC	-0.017	-0.012	0.00015	0.0034	0.0033	0.035	0.0057	0.9

Increased prediction accuracy: complex patterns and linkages in stock market data that traditional statistical approaches can overlook can be found by machine learning algorithms, particularly DL models. In time-series forecasting and pattern recognition, models like CNNs and LSTM networks have proven very successful.

Managing big datasets: from historical stock prices and trade volumes to economic indicators and sentiment data from social media and news, machine learning models are capable of processing and analyzing enormous amounts of data from a variety of sources. This thorough data analysis aids in the creation of more accurate forecasts.

Algorithmic trading: the creation of complex algorithmic trading techniques that can carry out deals quickly and often is made possible by machine learning. These algorithms have the ability to respond to market conditions in real-time, frequently quicker than human traders, which could result in increased earnings.

6. CONCLUSION

The developed study investigated the novel hybridized DL-based-CDConv-OGRU-framework for predicting stock movements using MI and historical prices. The developed model accurately learned the market news events and empirical price information by hybridizing circular dilated convolutions with the OGRU model. The developed model provided better orthogonality for enhancing generalization capability and eliminating gradient vanishing problems during training process. The developed method is processed and analyzed via the Python simulation platform. For experimentation, a publicly available StockNet database is utilized in this study and various performance measures like accuracy, recall, precision, MCC and f-score are computed and compared with other studies. In the experimental section, the developed method achieves the overall accuracy, precision, recall, F-measure, and MCC of 95.16%, 94.8%, 94.89%, 95%, and 0.9 respectively. However, the developed study focused only on stock predicting, it does not estimate the seasonality and time varying patterns for electricity consuming prediction models. Future research on automatic stock price movement prediction using CDCN-OGRU can focus on several key areas. These include integrating external economic factors like macroeconomic indicators to enhance prediction accuracy and developing methods to improve model explainability for better decision-making. Incorporating multi-modal data such as news sentiment and social media signals, as well as exploring hybrid models with reinforcement learning, could further improve the model's robustness. Other promising areas include applying transfer learning to low-volume stocks, optimizing risk management and portfolio strategies, enhancing real-time prediction capabilities, and utilizing blockchain technology for secure, transparent data management. These advancements could significantly improve the performance and applicability of CDCN-OGRU models in financial markets.

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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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