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An Integrated Blockchain Based Real Time Stock Price Prediction Model by CNN, Bi LSTM and AM

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Abstract

The continuous growth of blockchain has brought revolutionary impact on different areas with characteristics like decentralization, trust-worthy and tampering-proof. In the financial field, forecasting stock market had remained a challenging task for researchers. A novel integration of convolution and LSTM along with attention mechanism is proposed for prediction of stock price for the last hour of a day based it's performance in six hours for making prediction in intraday trades. The proposed prediction model uses 4 different stocks of Apple, Facebook, Nike and Uber for data input. The input data is given to the combination of many convolutional and LSTM layers for predicting future value of stocks in short term. Furthermore, the proposed model combines the obtained data with LSTM layers output vectors enhanced for final prediction. The prediction is based on past value of stocks. Performance evaluation is done based on RMSE and computational time. The average values obtained were 0.091 and 11.57 seconds respectively, showing it's superiority from benchmark models. The obtained data is stored on blockchain for enhanced security. The model can further be tuned for predicting other markets and will be more efficient than market specific markets.

Keywords: Smart Contracts, Convolutional Neural Network, LSTM, stock prediction

1. Introduction

The place where stocks are bought and sold are stock markets and they have a long history of being an important aspect of the economy. Investors in the stock market are interested in knowing any changes in stock prices,

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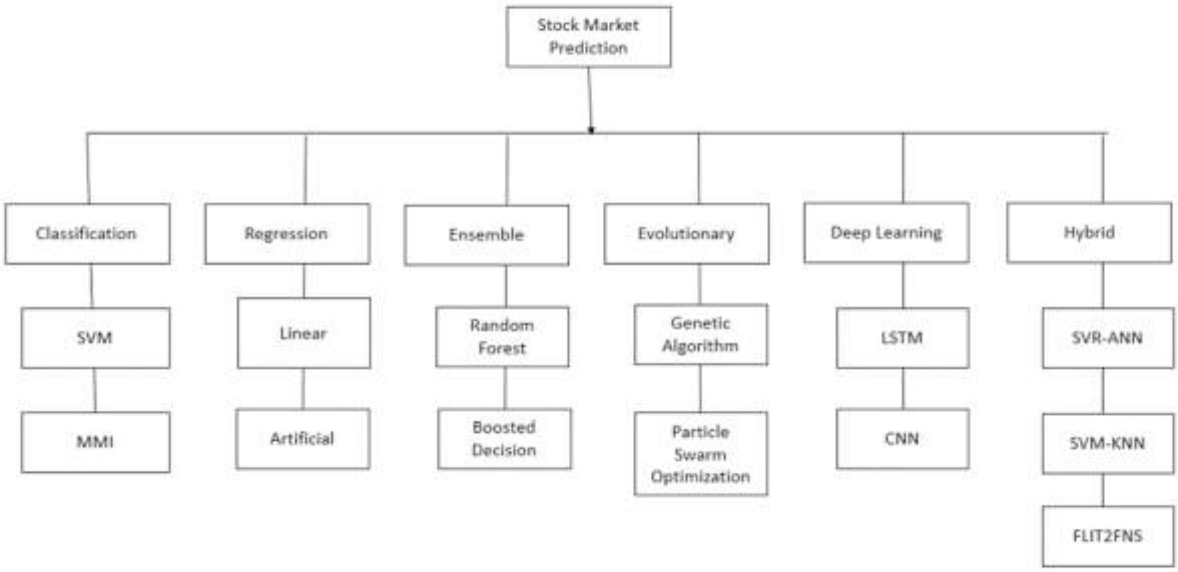


Figure 1: Different stock market prediction techniques.

accurately predicting stock prices can reduce investment risks for investors and help them make better investment decisions [1]. Different types of stock market prediction techniques are listed in Fig. 1. This paper provides an integrated approach of predicting stock prices by using a combination of CNN, BiLSTM and AM. The CNN extracts feature from stock data, the BiLSTM considers the interdependence of the obtained time series data, and the AM enhances the results by capturing the impact of past time series data. This paper presents an integrated multi-level neural network model for predicting the stock price at the last hour of trade based on study of stock movement for six hours. The presented model may help intraday traders to make correct decision in stock market.

1.1. Blockchain in stock market

A blockchain is a distributed, decentralized network that records all peer-to-peer transactions. In a blockchain, records are securely stored across many interconnected systems making blockchain technology more secure than centralised system [2]. A blockchain creates a permanent, verifiable and unalterable ledger by validating transactions across a distributed network [3]. Blockchain has the capacity to remarkably improve the efficiency of stock trades, especially by accelerating settlement processes. Presently, stock traders, representatives, and brokers undergo a time-consuming and expensive procedure that often takes couple of days to complete trades, mainly due to the involvement of intermediaries, complex operations, and regulatory requirements [4].

By harnessing the potential of blockchain technology, stock trades can be automated and decentralized, leading to heightened efficiency. Additionally, blockchain can offer advantages in fundraising, asset management, financing, trade settlements, securities lending tracking, and monitoring risk. Furthermore, it has the potential to reduce costs for clients and, in some instances, even eliminate the need for intermediaries entirely [5]. Blockchain-based solutions can address significant challenges in cross-border transactions finance by minimizing the number of intermediaries needed and providing greater geographical flexibility. With blockchain, traders can access stocks from any stock exchange or country as long as they are connected to the blockchain network, opening up new possibilities for seamless and borderless trading.

NASDAQ is promoting towards adopting blockchain in stock trades with DX exchange being the first company to offers digital stocks. ASX, an Australian stock exchange is planning to replace it with existing sub register systems for settlement clearing and exchange administrations. HKEX, a Hong Kong stock exchange is in early stages of blockchain implementation and has integrated with ASX for sharing information and experience. LSE, London based exchange has collaborated with tech giant IBM for providing open-source blockchain solution. These stock exchanges are integrating blockchain for enabling investors from other countries to invest in stocks listed in their countries [6].

Different blockchain based applications are commercially available for providing prediction facility to users in different domains. TotemFi is an Ethereum based stock prediction market. It consists of Ethereum smart contracts and Binance smart chain and provides non inflicting prediction and collaborative rewards. Augur is a blockchain boasting itself as a "global, no-limit betting platform" with giving users vast range of predictions opportunities on sports, economics, events and more. Omen.eth provide Gnosis tokens for providing anyone with ability of creating a prediction market in different domains ranging from crypto, sports, entertainment etc. PlotX is a cross-chain platform providing users ability of predicting crypto prices in hourly, daily and weekly times [7].

1.2. Equity Tokens

Similar to traditional stock asset, it represents a share that is the minimum trading requirement to be an investor in company. As any investor buy equity token it become part of the company and become entitled for any profit or loss with the company performance. Equity tokens differs from stock exchange only by means of providing ownership as traditional stock is logged into a database and listed in stock exchange but equity tokens record ownership on blockchain. Since, the equity tokens operates on blockchain they can operate on 24/7 allowing investors from different geographical locations to invest in stock markets as per their convenience [8].

Overall, blockchain has the potential to revolutionize the way stock market prediction is done making it an efficient alternative to improve the accuracy of predictions. Blockchain eliminate the chances of human error as blockchain smart contracts are written in a manner that they complete ignore human interactions and related errors. Blockchain also reduces the intermediaries fee due to automatic smart contract-based execution and also is free from government regulatory as investors can access the market globally without concerning geographical borders [9].

It is important to note that while blockchain technology offers several advantages for stock market prediction, its implementation may face challenges related to scalability, privacy, and regulatory compliance. Additionally, the success of blockchain-based prediction models relies on the availability of accurate and reliable data sources.

This paper focuses on following:

(1) An integrated method, CNN-BiLSTM-AM merged with blockchain is introduced for predicting stock price for the next hour.
(2) The obtained result is stored as equity tokens and are verified from original value of stock value.
(3) Comparison is done with six others already proposed ML models for future stock price prediction on same dataset, demonstrating the superiority of our model. the CNN-BiLSTM-AM method was found to be accurate and effective, making it a suitable choice for stock price forecasting.

The others sections of this paper are arranged as follows. The second part instigate related work of stock forecasting with their pros and cons followed by studies related with existing technologies in this field. Third part discusses the dataset being implemented for the work. The fourth part introduces the proposed methodology. The fifth validate the experimental results of correctness of the prediction with experimental results, along with describing how the data is being stored in blockchain for enhanced security and finally, the last part summarizes the experimental results and provide suggestions for future scope.

2. Background

The traditional method of stock price prediction used simple mathematical models such as simple linear models, including auto-regression and moving average model. However, as stock data can be influenced by many noise and uncertain factors, limitations of linear models became clear as the prediction period lengthened.

As a result, scholars turned to nonlinear models and implementing ML methods. Applying ML methods for stock price prediction is gaining popularity from researchers globally. Examples include using a neural network by White in 1988, but with limited success; Zhang's [10] use of a neural network and ARIMA in 2003 which showed that neural networks have an advantage in implementation of nonlinear data prediction but with lower accuracy; Nayak et al.'s [11] use of an artificially created chemical action based optimization algorithm for training multi-layer perception machine in 2015; Wang's [12] proposal of a wavelet neural network-based stock price forecasting method in 2017; Hu Yue's [13] use of CNN in 2018, which showed that CNN may predict time series and DL for eliminating time series problems; and Zeng et al. [14] use of BiLSTM in 2019, which showed that LSTM resulted in more accurate predictions than existing models. Kumar et al. [15] implemented a RNN classifier for predicting intraday stock price, provided detailed analysis of different technical price affecting parameters and founded an unknown pattern of stock movements by use of recursing feature elimination technique. Peng et al. [16] created a simple Dynamical and condition-based Heteroscedasticity problem with help of SVM for implementation on Ethereum blockchain. Analysis was done by implementing minimum and maximum recurrence inference, and were forecasted by implementing Dielbold–Matiano criterion. Their model considered different cryptocurrency data as input with considering individual at a time for predicting the future price.

Table 1: Summarized advantages and disadvantages of existing baseline models.

Technique	**Advantage**	**Disadvantage**
Integrated ARIMA and ANN model [10]	Successful in stock price prediction in nonlinear data prediction implementation	Lower accuracy
Adaptive Hybrid Artificially Chemical Reacted Neural Network ACRNN [11]	Different approaches to short-, mid- and long-term stock price prediction	Fails at higher order neural networks and hybridization scenarios.
Wavelet Neural Network [12]	Non-linear non-stationary financial time series	Failed at larger volume of stock
CNN and DL [13]	CNN predict time series and DL for eliminating time series problems	Prediction accuracy was insufficient
BiLSTM [14]	Problem of vanishing gradient and exploding gradient were eliminated	Only successful on large dataset on long term
CNN-BiLSTM-AM [14]	Real-time stock price prediction for next day closing price based on time series data	Longer training and testing time
RNN classifier [15]	Intraday stock price prediction	Lower performance of their intelligence system
SVR-GARCH's [16]	Predictive performance of daily and hourly volatility of three cryptocurrencies	Volatile nature of cryptocurrencies minimized accuracy of prediction

2.1. CNN

In 1998, a newer feed-forward neural network was implemented by Lecun et al. [17]. CNN has shown success in image processing and NLPs tasks. CNNs have also been implemented in time series prediction with positive results. Local perception along with weight sharing features of CNNs help to minimize the number of parameters, resulting in more efficient learning models. The architecture of a CNN typically includes three layered components: convolution, pooling, and full connection layers. Convolution layers contain multiple convolution kernels, and their calculations are defined in eq. (1). followed by features extraction. However, the number of feature dimensions extracted are huge, leading to the need for addition of pooling layer for reducing convolution layer feature dimensions and decrease training cost of network [18].

$$l_t = \tanh (x_t * k_t + b_t) \tag{1}$$

where l_t being convolution result; tan h is transfer function implementation; x_t being input vector, k_t being convolution kernel weight, and b_t being bias convolution kernel.

2.2. LSTM

LSTM is a network model introduced in 1997 [19]. It was implemented for addressing existing gradient explosion issues and disappearance in Recurrent Neural Networks. While a standard RNN has only one repeating module, typically a tanh layer, LSTM has four similar modules that interact in a unique manner [20]. Fig. 2 shows the LSTM architecture and is explained below.

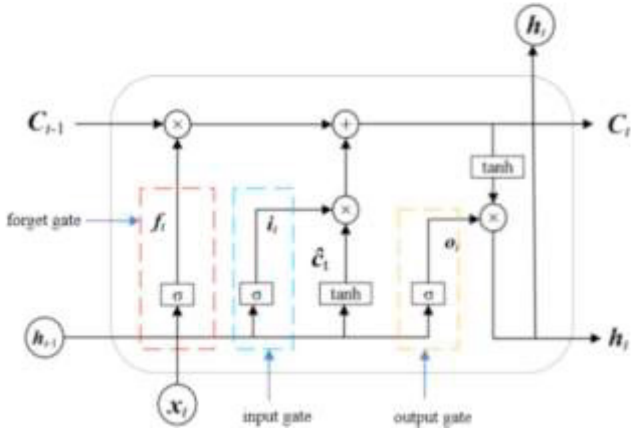


Figure 2: LSTM memory cell structure

The previous cell state C_{t-1}, and output value h_{t-1} from LSTM neuron unit, along with the current input, x_t, are used in the calculation process of LSTM. The activation function, r, is enforced for calculation of output forget gate, f_t, and the input gate, i_t, at present moment. The candidate cell, C_t, at the present moment is calculated based on these outputs. The output gate output, o_t, determines cell state, C_t, and output, h_t, of the present moment. The calculation process of LSTM involves these variables and operations.

2.3. Attention Mechanism (AM)

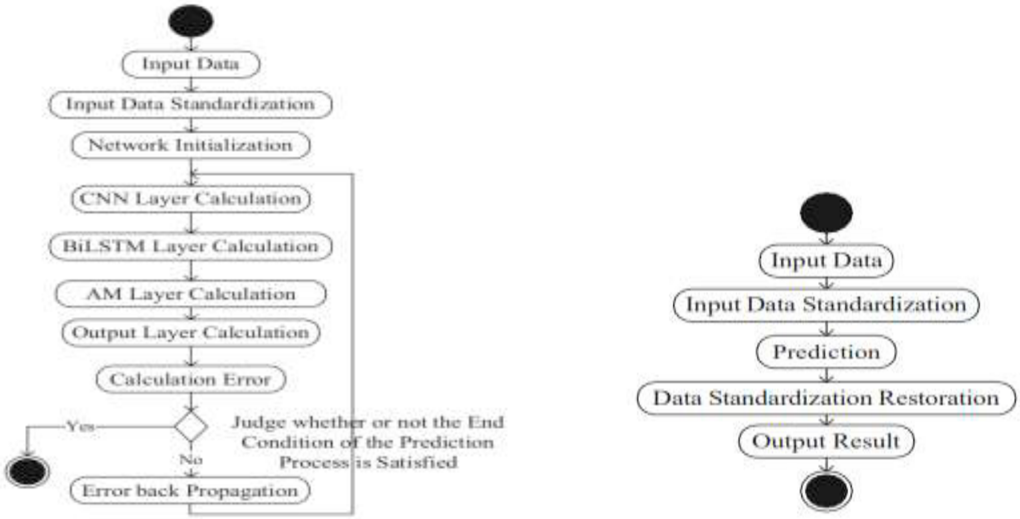
The AM is a computational approach utilized in deep learning models to improve the representation and comprehension of input data. It enables the model to concentrate on specific parts of the input that are considered most significant for the given task. This technique has found widespread application in various neural network architectures, including RNNs, Transformer models, and CNNs [21]. The fundamental concept behind the AM is to provide varying weights to different input, reflecting their relative importance. This selective allocation of attention allows the model to prioritize crucial elements and disregard less relevant ones, ultimately leading to enhanced performance and efficiency.

3. Dataset

In this experiment, for developing a blockchain based integrated stock price prediction model, the dataset is obtained from Yahoo finance obtaining data from four different companies of New York Stock Exchange (NYSE): Apple Inc., Facebook Inc., Nike Inc. and Uber Inc. [22]. These data were obtained from Yahoo Finance. For our model, we specifically utilized the stock every minute value for 8-hour stock market operations on 14^{th} April 2014 for training and testing the dataset.

4. Methodology

Our objective is to create a prototype for real-time stock price prediction. We divided the working period in eight hours, allocating a portion of this time for training and testing. Specifically, the aim was to correctly predict stock prices for next minute over the next 60 minutes, we utilized the initial 7 hours data for training and last 1 hour for testing. The training and testing model for real-time stock price prediction has been explained via flowchart in fig. 3.



(A) Training Process (B) Testing Process

Figure 3: Training and Testing process of proposed model

The main steps involved during the training state includes input data, its standardization, network initialization, CNN, BiLSTM and AM layer calculation followed by output layer calculation. The output layer output is then with real value for calculating corresponding error followed by judging whether end conditions of predictions were satisfied. If not, error back propagation in opposite direction, with weight and bias being updated. During testing phase, its follows a simple unidirectional approach to give the required output with major steps being input data and its standardization, prediction, standardization restoration and output.

5. Experiments

Our proposed method performance evaluation is done by four different stocks Facebook Inc., Uber Inc., Apple Inc. and Nike. The performance evaluation is done by calculating RMSE and computational time taken during the prediction. The obtained result is further compared with work done by different researchers working on same dataset for evaluating the performance more accurately. All model has been trained and tested with MATLAB software on an Intel i7- 4500H 2.7 GHz, 16 GB RAM on Windows 11 for evaluating the prediction parameters and determining the best window size, Root Mean Square Error (RMSE) is used as the evaluation criteria [23]. The formulae for RMSE calculation is given in eq. 2.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{\mathrm{Y}}_i - y_i)^2} \qquad (2)$$

where $\bar{\mathrm{Y}}_i$ is predicted and y_i is real value.

To ensure consistency, we maintained an equal dataset size of 430 rows for each stock. The models were trained for 80 epochs, and their performance was assessed based on the error and computation time. We stored the weight matrix for each epoch if the loss in terms of mean squared error was lower than the previous epoch. After completing the training, we tested the models on other 80 values and selected the one with the lowest RMSE as the final prediction.

For comparing our model, some baseline and advanced models have been taken into consideration. Both types of models have their pros and cons. For example, baseline model FBProphet is fast model but it produces higher errors in prediction, and hybrid model based on CNN and LSTM produces lower error prediction but takes longer times in making the predictions. This indicates that a single neural network model may performs satisfactory in one parameter but not in other. Therefore, we have implemented an integrated model with different multiple layer neural networks for exploiting the good features and eliminating the limitations. Only the models that had worked on similar dataset have been taken into consideration for providing a suitable comparison platform.

6. Results

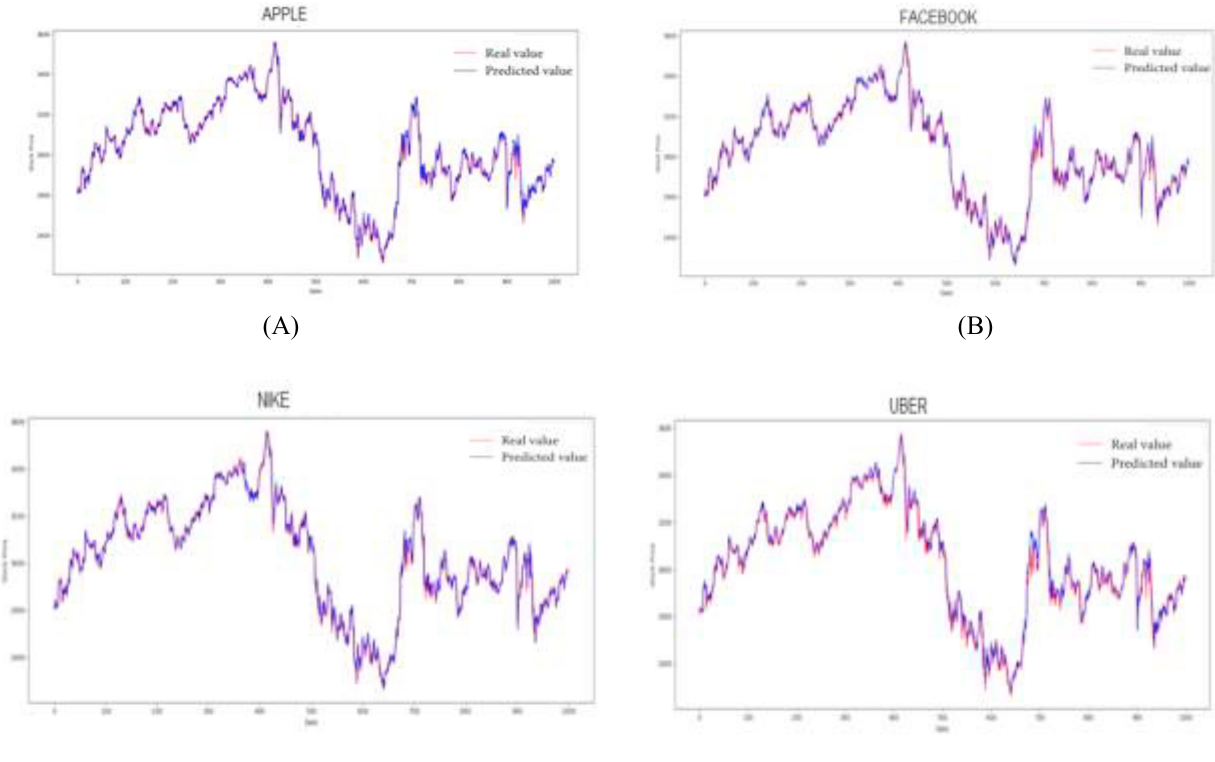
6.1. RMSE calculation

We conducted our experiments using a dataset consisting of 7-hour stock data values for training and 1 hour for testing. The prediction was made per minute making 420 training points and 60 test points. The performance evaluation was done considering the RMSE and computational time taken for stock prediction. Applying RMSE on all four stocks obtained yielded an output of 0.021, 0.014, 0.042 and 0.023 for Apple Inc., Facebook Inc., Nike Inc. and Uber Inc. stocks respectively. A comparison based on RMSE value with already conducted research for stock price prediction on similar dataset is listed in Table 2.

The training process of our proposed approach may be considered quick and reliable. It can be easily performed on CPU due to limited data-size. The proposed model has lower RMSE and faster computation times than other classical and hybrid models. This means that they can be used to make predictions of stock prices, which can help investors make more informed decision in intraday trades. A diagrammatic representation of variation in predicted and actual value is shown in Fig. 4.

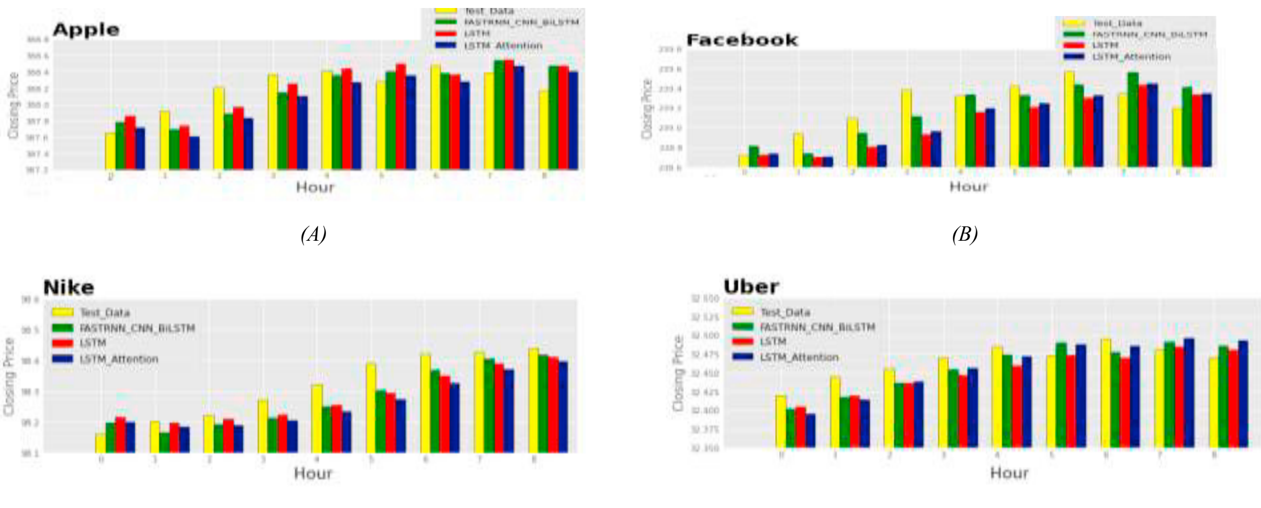
Table 2: RMSE and Computational time comparison with previously proposed model in Apple, Facebook, Nike and Uber Stock Values

Model	**Apple**		**Facebook**		**Nike**		**Uber**	
	RMSE	**Comp. Time**	**RMSE**	**Comp. Time**	**RMSE**	**Comp. Time**	**RMSE**	**Comp. Time**
ARIMA [8]	0.163	-	0.866	-	0.465	-	0.163	-
CNN2_LSTM2 [23]	0.025	17.894	0.169	17.293	0.071	18.389	0.025	17.894
CNN_BiLSTM [24]	0.021	17.225	0.171	17.228	0.052	18.375	0.021	17.225
FBProphet [25]	0.064	0.542	1.590	0.413	0.550	0.543	0.064	0.542
LSTM [26]	0.022	7.488	0.161	7.864	0.045	7.804	0.022	7.488
LSTM_Attention [27]	0.021	17.225	0.171	17.228	0.052	18.375	0.021	17.225
Proposed	**0.021**	**11.734**	**0.014**	**10.910**	**0.042**	**11.8980**	**0.023**	**11.747**



(A) (B) (C) (D)

Figure 4: Comparison between real and predicted value from our model for stocks of (A) Apple (B) Facebook (C) Nike and (D) Uber



(A) *(B)* *(C)* *(D)*

Figure 5: Predicted stock values with our proposed model and baseline models *of* (A) Apple (B) Facebook (C) Nike and (D) Uber

6.2. Blockchain storage

Ganache, an Ethereum simulation software with all RPC and functions, feature and events for developing dApps has been implemented for simulating the storage of predicted values on blockchain. It provides an already created networks with 10 different accounts with 100 ethers in each account. Figure 6 shows storage of our predicted values on Ganache software [28].

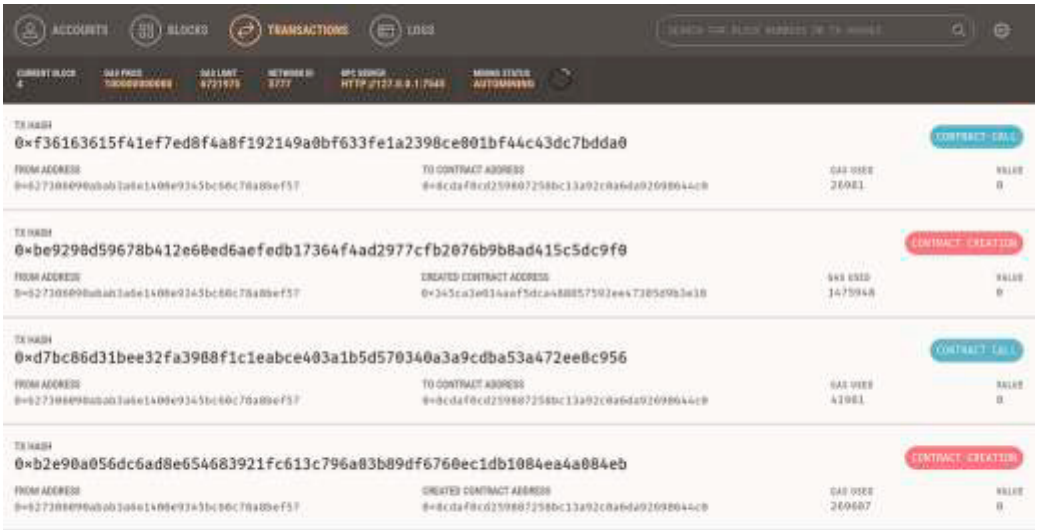


Figure 6: Ganache implementation for predicted value storage on blockchain

7. Conclusions

This research introduces a CNN-BiLSTM-AM, for predicting the stock price at last hour of day based on study of every minute's stock progress for 420 minutes and prediction price for next 60 minutes. This could prove to be very beneficial for trader in intraday transactions. The CNN component is employed for extracting relevant features from input data, and the BiLSTM component is utilized to learn and forecast these extracted features. Additionally, the AM component captures effect of temporal features in the time series data, thereby enhancing the prediction capability of the model. The RMSE obtained from the stock were 0.021, 0.014, 0.04 and 0.023 making an average of around 0.098, making it a better alternative of stock price prediction from existing benchmark models. These findings highlight the importance of employing a complex network architecture for achieving high prediction accuracy.

In near future, focus would be on adjusting the performance parameters for making the prediction models more accurate. Our prediction model would also implement in more prediction in different application domain such as time series, gold price, weather, earthquake and many more.

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Conflict of Interest: The authors declare that they have no conflict of interest.

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